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# Asset Management DataInfrastructures

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# Asset Management Data Infrastructures

**Proefschrift**

ter verkrijging van de graad van doctor

aan de Technische Universiteit Delft,

op gezag van de Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen;

voorzitter van het College voor Promoties,

in het openbaar te verdedigen op

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door

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This dissertation has been approved by the promotors.

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# Preface and Acknowledgements

Many organizations tasked with managing public utility infrastructure routinely collect and store large volumes of data for decision making purposes in their management and maintenance processes. This data is collected, stored and analyzed within data infrastructures, however, traditional data management methods are becoming increasingly inadequate. More and more, data is being provided by new sources that can communicate over the internet, collectively known as the Internet of Things (IoT). IoT devices and the communication between these devices may benefit the management of public utility infrastructures by providing enough quality data to generate trusted information required to make the right decisions at the right time, helping asset management organizations improve their decision making capability. However, current asset management data models tend to view the system from a static perspective, posing constraints on the extensibility of the system, and making it difficult to adopt new data sources such as IoT. The extensible data infrastructure model presented in this dissertation aims to help improve our understanding of modern asset management, to identify risks of IoT adoption in asset management and to provide actionable insights for the achievement of expected benefits of IoT adoption in asset management organizations.

The development of the model and this thesis was only possible due to the very many people who freely gave of their time, knowledge and expertise. A book is never written by just one person. It is the work of many. It is the result of endless discussions and encouragements. Of hours of interviews, corrections and re-writes. Of making room and giving space. Of time given freely. Help has come from many places, known and unknown - all contributing for no reason other than a desire to see this project succeed. I have been humbled and my gratitude is deep.

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Jelle introduced me to Marijn Janssen and Paulien Herder, my two extremely hard-working, long suffering and truly brilliant promotors,

guides and mentors. It is hard to be too effuse when expressing my gratitude and admiration for these two amazing people. Not only are they brilliant scientists, they are also simply kind and big-hearted people and it has been an honor to have worked with both. Marijn and Paulien, thank you for your guidance and your friendship.

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Of course, all this did not occur in a vacuum. Especially as my "little hobby" was written mostly outside of working hours. I am unbelievably lucky to be surrounded by the most special support group of family and friends. To my friends, you are all loved and appreciated.

To my parents, thank you for providing me with a loving home, support and encouragement in all my endeavors and the best education in the world. It is your foundation which I have been able to build on. Dave and Judy, Debbie and Dan, Boudewijn, Ella, Saar, Ewout, Francesco, Nina and Thijs, Lyrah and Bella, Teagan and Makayla, thank you all for your personal support!

To my other brother, best man and paranymph, Stoff – thank you for being there when I need you. The love is deep.

To my children, Sacha and Owen, who have not yet known a Papa who wasn't studying. You fill the deepest parts of my heart. Thank you for your patience and for showing me what is most important in life.

Finally and most importantly, to my wife, Merijn. You are my best friend. You let me go when I need to, and bring me back when I am lost. There are no words. I could not have done this without you. Thank you. I love you.

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# Chapter 1 Introduction

*"There is a tide in the affairs of men.*
*Which, taken at the flood, leads on to fortune;*
*Omitted, all the voyage of their life*
*Is bound in shallows and in miseries.*
*On such a full sea are we now afloat,*
*And we must take the current when it serves,*
*Or lose our ventures."*

**- William Shakespeare (*Julius Caesar: Act-IV, Scene-III*)**

## 1.1 Introduction

The proper management and maintenance of public utility infrastructures is vital to economic prosperity. These infrastructures consist of networks of assets and are often managed by organizations using an asset management approach. Successful asset management is heavily dependent on information, requiring large amounts of quality data. This data is managed in *asset management data infrastructures* (AMDIs). More and more, new technologies such as the *Internet of Things* (IoT) are becoming available and are being adopted by asset managers to provide the required data. However, adopting IoT in asset management organizations is a non-trivial undertaking. Design solutions that guide asset managers in understanding asset management through IoT are needed to ensure that asset managers continue to be supplied with the right information at the right time. This research therefore seeks to improve our understanding of asset management through IoT adoption and we ask what the benefits and risks of IoT are for asset management. There is only limited research on AMDIs and models which improve understanding of asset management through IoT are missing. Therefore, we aim to improve our understanding of asset management through IoT by describing a model of AMDIs which accommodates IoT adoption.

The underlying premise of this research is derived from the Duality of Technology theory (Orlikowski, 1992), suggesting that IoT will introduce unexpected changes within asset management. The dual nature

is that the introduction of IoT as a technology introduces unexpected changes to the people, business processes and the organization, which then, in turn, may also lead to developments in the technology. Second, we acknowledge the complexity of AMDIs and view AMDIs as Complex Adaptive Systems (CAS). On the basis of the insights provided by duality of technology theory and CAS theory, we develop a model of AMDIs which improves understanding of asset management through IoT and provides actionable insights into previously unforeseen changes so that asset managers are able to take appropriate action as the AMDI evolves.

This chapter is structured as follows: section 1.1 introduces the research; sections 1.2 and 1.3 discuss the societal and scientific impact of the research; section 1.4 discusses the research drivers; sections 1.5 and 1.6 discuss the research objective and the research questions; and section 1.7 shows how this dissertation is organized. The reader should note that parts of this chapter have been published in: Brous, Janssen & Herder, (2018) "Internet of Things adoption for reconfiguring decision-making processes in asset management", Business Process Management Journal.

### 1.1.1 Problem Statement

Infrastructure supports all forms of modern living and is vital for creating economic prosperity, but is often taken for granted until something fails (Herder, de Joode, Ligtvoet, Schenk, & Taneja, 2011). Furthermore, environmental stresses, such as climate change or socio-demographic and financial constraints, introduce complexity to infrastructure management (Herder et al., 2011). In order to ensure that the management of essential infrastructure is able to withstand these stresses, an overarching view of infrastructure networks throughout the entire asset lifecycle is required. More and more, organizations are looking to asset management to provide this overview (Koronios, Lin, & Gao, 2005). Asset management views infrastructure management as an asset lifecycle, providing the foundation for a coordinated approach to managing the infrastructure in its entirety (Mehairjan, 2017). It ensures that essential infrastructure receives appropriate investment and attention and has the appropriate resilience to meet new challenges.

According to ISO 55000 (2014), an asset is an “item, thing or entity that has potential or actual value to an organization”. The term, “asset” in this paper refers to physical public utility infrastructure assets. Asset management is important for the management of infrastructure industry as the success of an asset management organization often

depends on its ability to use and manage its assets efficiently (Koronios et al., 2005).

However, asset management requires large amounts of data to drive decision-making. Data-driven decision-making in asset management means preventing unwanted events and making decisions based on analytical models. Rapid technological advancement in sensor-based data collection techniques enables us to gather an ever-increasing amount of detailed and relevant data. Adopting IoT in order to increase these capabilities can increase the potential for improving performance at all levels, but expectations and pitfalls also increase exponentially. Data mining (the search for statistical connections in databases), for example, has already been embraced by several sectors such as marketing, medical care, ICT and finance (Linoff & Berry, 2011), but its implementation in the asset management arena is so far limited. Asset management organizations are beginning to develop sensor-based data collection, but the maturity of the sector in IoT adoption is low, despite the wide-spread expectation that IoT may provide a variety of benefits for asset management processes. For example, water management organizations require a better understanding of the added value that data-driven analytical methods could represent for them, and seek a knowledge base to guide them in implementing data-driven decision-making in asset management (Bessler, Savic, & Walters, 2003).

Due to the steady increase in the numbers of sensors in networks, more and more opportunities are becoming available to employ data-driven decision-making to answer questions of relevance to the asset management sector. For example, geospatial data-mining can be used to assess hidden relationships of the crisis and environmental pollutions, sources, causes and amount of pollutions to take necessary measures for environmental protection (Karimipour, Delavar, & Kinaie, 2005). However, there are a number of challenges that need to be overcome in order for asset managers to be able to fully trust the data being generated by IoT. It is insufficient to only implement an IoT solution and expect asset managers to trustingly adopt the results and change their decision making processes without protest (Can Duzgun, 2017; Spiegeler, 2017). For example, asset managers need to be able to understand the data in their possession. Furthermore, the development of many modern public utility infrastructure assets began many years ago and the data on these assets may be incomplete or provide conflicting reports.

The information challenges faced by asset management organizations (such as poor data quality) are increased by the fact that organizations have often changed significantly over time, leading, for

example, to a highly complex system architecture. Many organizations have lost the ability to fully understand how their assets contribute to the delivery of their value streams. In addressing asset performance in one area, it is not possible to know how that will affect asset performance elsewhere or across the system as a whole. Analytics is also often hindered by data availability and data quality. How asset management organizations respond to these data quality challenges determines their own effectiveness, and the effectiveness of the infrastructures they manage. For example, adverse effects of data-driven asset management are often related to the lack of capability within the organization to efficiently manage their IT infrastructure. The issue of data-driven asset management is becoming more complex as data systems in asset management organizations develop toward distributed, cloud-based data environments in which data is stored in different places across different platforms.

Asset management through IoT can provide a multitude of benefits to asset management organizations, but it also introduces new risks and challenges. For example, it is now possible to automatically monitor overloading by freight trucks, and to automatically send fines to offenders, but this capability also raises the need for data privacy and data security solutions to protect the privacy rights of citizens. This *ethical question* not only requires a technological solution, but also requires a legal framework to provide guidelines and enforce accountability of compliance. With accountability comes the need for governance of the data as well as strong data policies and data management processes. This often requires knowledge and organizational structures that may not be immediately available in an organization. Fulfilling this need often requires structural changes to the organization. In addition, organizational structures sometimes block the gaining of benefits. The dual nature of IoT suggests the necessity of organizational change to be able to reap the full benefits of IoT adoption.

As such, in order to manage infrastructure assets successfully, having data about assets over their entire lifecycle is of paramount importance (Lin, Gao, Koronios, & Chanana, 2007). For this, a data infrastructure that captures the data representing the infrastructure is needed, as shown below in Figure 1-1. In Figure 1-1 we see that not only do asset management organizations need to develop data about their physical assets (within their AMDIs), but that the data also needs to be managed in keeping with the management of the assets themselves.

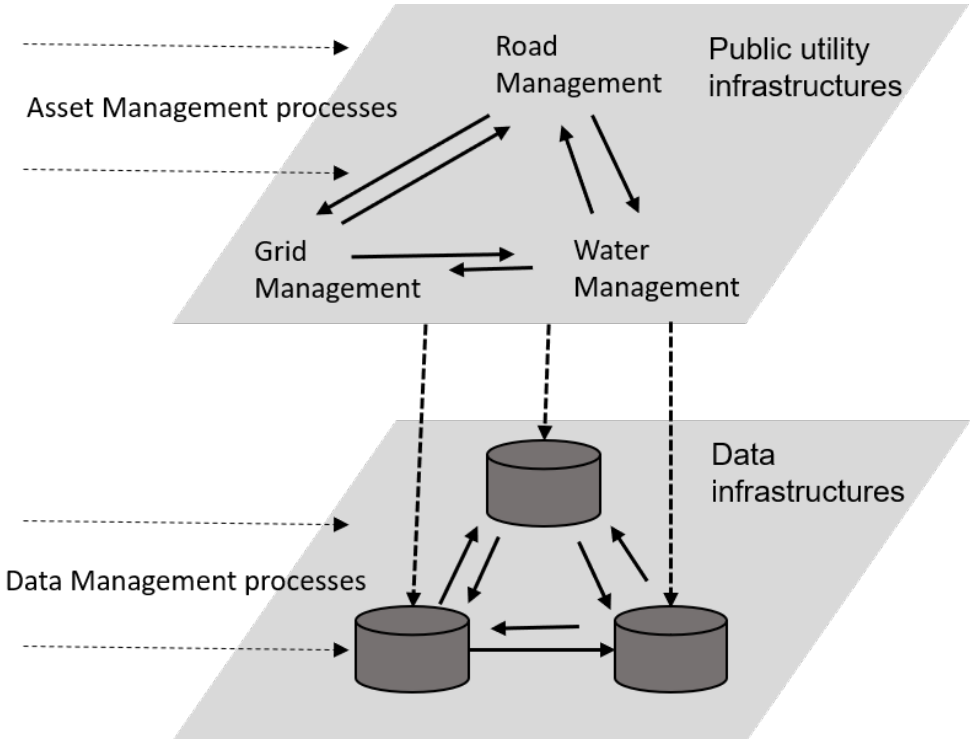


Figure 1-1: The relationship between asset management and data infrastructures

All AMDIs have a unique character and behave differently. This makes it difficult to implement AMDIs in different environments and achieve similar outcomes (Grus, Crompvoets, & Bregt, 2010). AMDIs have been identified as CAS (Grus et al., 2010), and using a CAS lens can help us to identify and better understand the key characteristics of data infrastructures (Brous, Overtoom, Herder, Versluis, & Janssen, 2014). According to Auyang (1999), CASs are often built from individual agents which adapt as they interact with each other and their environment. Conceptualizing AMDIs as CAS means that it is possible to gain a better understanding of their relevant dependencies (Janssen & Kuk, 2006). Conceptualization as CAS acknowledges that it is impossible to exert a hierarchical control over complex systems of organizations and projects spanning multiple levels and jurisdictions. Instead, one must take into account the various typical characteristics of CAS (Herder, Bouwmans, Dijkema, & Stikkelman, 2008). This uncertainty and the level of complexity suggest that AMDIs should be designed to perform acceptably over a larger class of situations than was anticipated by their designers (Sussman, 2007). Because AMDIs are complex, there is an

interrelationship between their sociological and technical dimensions, and it is difficult to track cause-and-effect relationships. The dynamic sociological and technological interrelations between agents and the components of AMDIs are therefore hard to predict and control.

### 1.1.2 Relevance

Public utility infrastructure is developed over many years, and decisions regarding this infrastructure have to be made in the midst of a good deal of uncertainty regarding the future (Herder et al., 2011). There are many variables that may change over the course of time such as technological advances, political shifts, or changing stakeholder and economic fluctuations. These complexities have only increased over the course of time, greatly increasing the risks involved such as spiraling costs, or system failure (Herder et al., 2011). More and more, modern asset management organizations are relying on data and information to help them make decisions in order reduce these risks, improve efficiency and achieve their business objectives (Herder et al., 2011). As such, new technologies such as IoT are gaining wide popularity and attention as asset managers seek new ways to gather the data required to be able to optimize asset management processes.

The implications of applying data-driven asset management to managing infrastructure shows why it has become important for asset management organizations to incorporate successful data management techniques and processes to ensure consistent, reliable service delivery. For example, if decision-making is based on data of poor quality, then there is a high risk that the decision being made may be flawed, leading to re-work and damage to an organization's reputation.

Many asset management organizations are faced with limited financial and human resources that must be directed at maintaining and renewing infrastructure, and dealing with changes in demand (Herder et al., 2011). For example, the challenges faced by water management organizations in meeting their statutory responsibilities are well known. Water management organizations often struggle to fulfil their asset management obligations as set out by the European Water Framework Directive. As such, mature levels of data management are becoming essential for successful asset management, and can help strengthen the development and operation of public utility infrastructure networks and the services provided to the community to ensure long-term sustainability. As data management and data governance matures, asset managers are beginning to leverage IoT techniques to provide more visibility into existing infrastructure and greater predictability into

potential changes (Brous, Janssen, Schraven, Spiegeler, & Duzgun, 2017). In this way, the organization may gain greater productivity across all of its assets and can begin to manage infrastructures in a more cohesive manner. Data-driven asset management is increasingly expected to drive business processes; either by increasing productivity or finding opportunities through data analysis that were previously unknown (Brous, Janssen, & Herder, 2018).

### 1.1.3 Developments

Public utility infrastructure systems, such as water management systems, provide many of the services that are vital to the functioning, and security of society, and managing these assets effectively and efficiently is critical (Tien et al., 2016). As such, more and more extensive ranges of physical and social sensors to detect damage and monitor capabilities are being introduced into many of these systems. The goal behind the introduction of the sensors is to gain a greater understanding of and control over the performance and quality of assets (Aono, Lajnef, Faridazar, & Chakrabartty, 2016; Tien et al., 2016). IoT refers to the increasing network of physical objects that feature an IP address for internet connectivity and the communication that occurs between these objects and other Internet-enabled devices and systems (Hounsell, Shrestha, Piao, & McDonald, 2009; Ramos, Augusto, & Shapiro, 2008). IoT makes it possible to monitor and control the physical world from a different location to that of the physical object, allowing many physical objects to act in unison, through means of ambient intelligence (Ramos et al., 2008).

Technology and society influence each other in many ways, and analytical efforts to treat these as distinct conceptual units are increasingly being called into question (Boos, Guenter, Grote, & Kinder, 2013). A structured approach to the interaction of human and technology such as described by the duality of technology theory (Orlikowski, 1992) is therefore proposed in this research as being necessary to gain an understanding of the sociological and technical interrelations between agents and technological components of AMDIs which are enabled by IoT. The duality of technology theory (Orlikowski, 1992) describes technology as assuming structural properties whilst being the product of human action. Actors physically construct technology in a social context, and attach different meanings to it, and technology develops from the ongoing interaction of human choices and institutional contexts (Orlikowski, 1992).

IoT adoption in asset management organizations is expected to bring many benefits, but may also introduce risks of possible future

consequences that go beyond the intended. The duality is that the gaining of some technological benefits might also have unintended social effects on the organization. For example, IoT allows organizations to develop and improve services that cannot be provided by isolated systems. However, the organizational structure might be impacted as the technology forces changes to asset management business processes.

As IoT is further adopted, it is seen by many as very likely that asset management will be able to leverage the data and insights that IoT provides (Andersen, Christiansen, Crainic, & Grønhaug, 2011; Hua, Junguo, & Fantao, 2014; Lee, 2014). IoT covers a range of technologies, and asset management platforms could possibly drill down into not only server, storage and networking infrastructures, but also monitoring devices, sensors and even mobile and wearable systems. Many asset management organizations are exploring IoT technology as a way to solve their increasingly complex challenges. (Hua et al., 2014; Lee, 2014).

In order to increase trustworthiness of data, data governance has recently received widespread attention from practitioners as organizations are becoming increasingly serious about the notion of "data as an asset". Many academic sources (e.g. Fruehauf, Al-Khalifa, Coniker, & Grant Thornton, 2015; Khatri & Brown, 2010; Otto & Weber, 2011; Wende & Otto, 2007; Wende, 2007) follow the information governance definition of Weill & Ross (2004) and define data governance as "specifying the framework for decision rights and accountabilities to encourage desirable behavior in the use of data" (Wende, 2007, p. 418).

Figure 1-2 below shows that data governance may play an important role in coordinating the changes to AMDIs when IoT is adopted in asset management organizations.

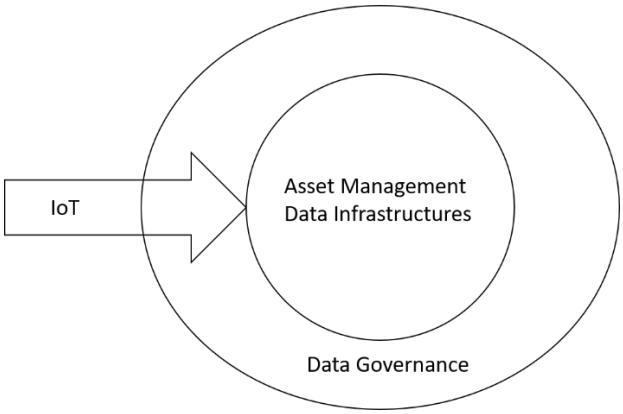


Figure 1-2: The role of data governance in AMDIs

Data governance is about coordinating data management - identifying the decisions regarding data that need to be made and who should be making them. However, principles for data governance that deal with specific issues regarding the coordination of IoT data within asset management are missing. Data governance principles provide insight into how the integration process of IoT into asset management may be effectively coordinated.

## 1.2 Societal Contribution of the Research

The societal relevance of the research becomes clear when the opportunities provided and the threats of missing opportunities are viewed. Efficient and cost effective development and coordination of data infrastructural elements can be regarded as a potential source of competitive advantage. In 2014, the then Vice President of the European Commission, Neelie Kroes, argued that data is crucial for the economic development of the European Union, citing a possible yearly market of €27 billion within the EU alone (Herder et al., 2011). Being able to align and utilize the available data with current and future requirements can have an immediate impact on the performance of asset management organizations. Large-scale data gathering and analytics are quickly becoming a new frontier of competitive differentiation (Herder et al., 2011), and organizations tasked with managing large scale, public utility infrastructure are increasingly looking to data to drive their asset management decision making processes. This data is created and managed within AMDIs. However, integrating IoT data sources into existing asset management data infrastructures is a complex undertaking. The major contribution to society that this research brings is to develop a model of AMDIs that improves understanding of asset management through IoT and helps asset management organizations to mitigate risks and achieve the expected benefits of IoT adoption.

IoT data can be used in many ways, such as determining one's position or sensing the temperature to ensure that gauges are configured correctly and that temperatures remain within accepted norms. IoT can benefit asset management organizations by providing enough quality data to generate the information required to help asset managers make the right decisions at the right time. IoT also makes it possible to access remote sensor data and to monitor and control the physical world from a distance, allowing many physical objects to act in unison, through means of ambient intelligence. However, despite these apparent benefits, the current adoption of IoT remains low and expected benefits are often not

achieved. Technology and society influence each other in many ways, and approaches which treat these separately are increasingly being called into question. To achieve the expected benefits of asset management through IoT, a pragmatic approach to the interaction of human and technology is therefore required. This research improves understanding of asset management through IoT by investigating and describing elements and behaviors of AMDIs which accommodate IoT data sources and suggests practical approaches to reduce the risks that IoT adoption imposes. As such, the elements and behaviors of AMDIs are described in this research in a model of AMDIs which accommodate IoT.

Understanding technology as continually being socially and physically constructed requires discriminating between human activity that affects technology, and human activity that is affected by technology. This research defines requirements for effective and sustainable development of AMDIs in asset management organizations and suggests that the inherent complexity of AMDIs requires data governance which encourages desirable behavior in the use of data. Because there is a dependence on interactions between elements of AMDIs, the ability to coordinate the management of data is essential to their development.

In essence, the societal impact of this research is that it addresses the need to improve understanding of asset management through IoT, to help achieve benefits of IoT adoption in AMDIs and to mitigate risks by describing a model of AMDIs which accommodates IoT. The model also outlines principles and guidelines for data governance in asset management organizations to help guide coordination of IoT data management in AMDIs. The inherent complexity of adopting a data driven approach to asset management requires an effective data governance strategy to ensure data quality, manage expectations, build trust and integrate IoT data in AMDIs.

## 1.3 Scientific Contribution of the Research

This research shows that IoT will introduce a variety of changes to asset management. Application of Duality of Technology theory (Orlikowski, 1992), confirms the dual nature of asset management through IoT. Many studies on asset management through IoT tend to focus on a single dimension such as organizational factors, as organizational factors are often thought to be the main drivers of innovation adoption in organizations (Subramanian & Nilakanta, 1996). However, IoT both enables and constrains asset management. This dual influence has not yet been recognized in studies that attempt to determine whether IoT

adoption has “positive” or “negative” effects on asset management. Orlikowski's (1992) framework allows us to recognize that IoT necessarily has both restricting and enabling implications for asset management organizations. Which implication dominates may depend on a variety of factors, including the autonomy, capability, actions and motives of the actors implementing and using IoT, as well as the organizational context within which IoT is adopted (Orlikowski, 1992). It is assumed that IoT has much potential for asset management, however, evidence of how IoT impacts the asset management organization remains largely anecdotal. Expected benefits of IoT in asset management may introduce unexpected risks and, as suggested by the duality of technology (Orlikowski, 1992), IoT may become part of the structures which constrain individual actions. For example, adopting IoT for access control to public transportation may improve efficiency, but removing the human element of conductors in trains and busses may introduce unexpected risks such as increased incidences of vandalism, requiring new organizational structures to mitigate these risks. There is a need to address the potentially unanticipated impacts of IoT adoption (Ma, Wang, & Chu, 2013; Neisse, Baldini, Steri, & Mahieu, 2016) and to systematically investigate the impact of IoT on asset management (Haller, Karnouskos, & Schroth, 2009). This research fills that gap by undertaking a systematic review of expected benefits and unexpected risks of asset management through IoT and conducting exploratory case studies to fill the gaps in the current knowledge base.

This research also builds on the work of research into data infrastructures as CAS (Grus et al., 2010; Hanseth & Lyytinen, 2004; Hanseth, Monteiro, & Hatling, 1996; Little, 2003; Ottens, Franssen, Kroes, & Van De Poel, 2006), with special regard to IoT its effect on traditional asset management. Because of their socio-technical constructs (de Man, 2006; Grus et al., 2010; Hanseth et al., 1996) we follow Grus et al. (2010) and adopt the perspective that AMDIs are complex, adaptive systems which by their very nature accommodate multi-actor involvement. As such, this research extends the body of knowledge of information science by describing a CAS framework to investigate the AMDI phenomenon. Researchers have increasingly approached physical infrastructures as being CAS, but although physical infrastructures are often approached as CAS, their underlying AMDIs hardly are. AMDIs are complex socio-technical systems and there is a need to understand how AMDIs evolve and adapt to new, disruptive technologies such as IoT (Haller, Karnouskos, & Schroth, 2009). For example, adoption involves more than a decision to implement IoT, but also includes the staff’s

acceptance and initiation of their individual processes of accepting the innovation (Frambach & Schillewaert, 2002). An important omission in the identification of phases of adoption (Damanpour & Schneider, 2006) is that of the end-state and post-adoption. This research fills this gap by including the end-state and post-adoption phases of asset management through IoT in the investigation. Attention is also necessarily given to the process leading to acceptance of IoT. This research therefore investigates how current asset management organizations are responding to IoT through the development of an AMDI model that accommodates IoT.

When faced by change, actors may anticipate the consequences of their actions and develop rules to adapt to these consequences. There is a need to investigate these rules in the AMDI and research how they affect the asset management organization and how they are interpreted as data governance (Thompson, Ravindran, & Nicosia, 2015). This research extends the body of knowledge surrounding data governance in asset management by being the first to investigate the phenomenon of data governance within asset management organizations and how data governance may coordinate data management in an IoT setting. Because there is a dependency on interactions between technical and social elements, the ability to coordinate the management of data is essential to asset management through IoT. Coordination emphasizes two methods for the improvement of data flows: the coordination of activities, and the coordination of commitments (Janssen, 2001). Although scant attention has been paid to coordination of data management in asset management organizations, there have been several calls within the scientific community for more systematic research into data governance and its impact on the information capabilities of asset management (Fruehauf et al., 2015; Hashem et al., 2015; Otto, 2011a). Little evidence has been produced so far indicating what actually has to be organized by data governance and what data governance processes may entail (Otto, 2011a). Most research into data governance until now has focused on structuring or organizing data governance. Evidence is scant as to what data governance entails (Fruehauf et al., 2015; Hashem et al., 2015). The principles of data governance in asset management we present in this research attempt to fill this gap.

## 1.4 Research Drivers, Concepts and Definitions

This section presents the background of the various domains, theories and concepts relevant for this research. In section 1.4.1 we discuss asset management and asset management organizations; in section 1.4.2. we

discuss data and information; in section 1.4.3. we discuss AMDIs; in section 1.4.4 we discuss IoT; in section 1.4.4 we discuss data governance; and in section 1.4.5 we discuss adoption of IoT.

### 1.4.1 Asset Management and Asset Management Organizations

Infrastructure networks are networks of assets that serve defined communities where the system as a whole is intended to be maintained indefinitely to a specified level of service by the continuing replacement and refurbishment of its components. One of the most important features of infrastructure networks is the degree of inter-dependency, not only within a particular asset network, but also from one network to another (Hastings, 2010; Volker, Altamirano, Herder, & van der Lei, 2011). The failure of one component within a network may undermine the ability of other networks to perform. For example, a water main burst may disrupt traffic on a city street. According to Hastings (2010), the goal of infrastructure asset management is to cost effectively maintain a service at a certain level, by managing the assets for present and future uses.

The basis of asset management is to be able to apply technical and financial judgement and sound management principles to decide which assets are required to meet business objectives, to acquire those assets and to maintain those assets throughout their entire lifecycle, including their disposal. Asset management gives an organization the knowledge and tools to develop and maintain the infrastructure under its management (The Institute of Asset Management, 2011). Figure 1-3 below shows how asset management fits into the asset management organization according to the ISO 55000 standard. ISO 55000 is an international standard covering management of physical assets. ISO 55000 (https://www.iso.org/obp/ui/#iso:std:iso:55000:ed-1:v2:en) defines *asset management* (AM) as the "coordinated activity of an organization to realize value from assets". AM is also understood to be "the set of activities of a business objective associated with: identifying what assets are needed; identifying funding requirements; acquiring assets; providing logistic and maintenance support systems for assets; and disposing or renewing assets so as to effectively and efficiently meet the desired objective" (Hastings, 2010 p. 6).


Figure 1-3: Managing Assets and the Organization: ISO 55000, clauses 3.2.4, 3.3.1, and 3.4.3

The objective of AM is to ensure the infrastructure functions safely, effectively and efficiently, given the constraints of the costs involved (Mohseni, 2003). AM is therefore essentially a matter of understanding risk, followed by developing and applying the correct business strategy, and the right organization, process and technology models to solve the problem (Mohseni, 2003). In this research we follow ISO 55000's definition of AM as being the "coordinated activity of an organization to realize value from assets".

**Definition 1.1:** asset management is the coordinated activity of an organization to realize value from assets.

Maximizing value and minimizing risk are important drivers for optimization of the asset portfolio and system (Volker et al., 2011). Asset management organizations should have AM as a primary process. For this research, we define an asset management organization as an organization tasked with managing and maintaining public utility infrastructure and which recognizes AM as a primary process.

**Definition 1.2:** an asset management organization is an organization tasked with managing public utility infrastructure.

The activities associated with AM are: identifying what assets are needed, identifying funding requirements, acquiring assets, providing logistic and maintenance support for assets and disposing or renewing assets (Hastings, 2010). These activities provide the scope for this research. According to (Mehairjan, 2017), from a business point of view, AM has the following goals:

- Balance cost, performance and risk,
- Align capital and operational spending decisions and corporate objectives and
- Make fact-based and asset data-driven decisions.

AM is widely argued in the literature as an *umbrella* subject which can encompass many aspects for the management of asset intensive industries (Mehairjan, 2017). In this research, AM is described in the context of infrastructures or physical AM.

### 1.4.2 Data and Information

The term "data" is often used in everyday terminology to refer to either raw data or to information (Khatri & Brown, 2010; Lin et al., 2007; Wende & Otto, 2007). According to Ackoff (1971), data are symbols that represent the properties of objects and events, whereas information consists of processed data, the processing directed at increasing its usefulness. A complication is that from an information systems perspective, data and information can both take digital forms and, in these forms, are often, in practice, collectively referred to as data. For example, in an IoT environment, sensors such as temperature gauges make observations or measurements about an object or its environment, which may be registered in a system and is often referred to as raw data. This data can also often be enriched with other descriptors that help identify an object or thing, or, the environment, infrastructure, system, or network in which the sensors, object or thing can be found. An example of this would be a name given to a person or object. In this research we follow Ackoff (1971), and define data as symbols which represent the measure or description of objects or events.

**Definition 2.1:** Data are symbols representing measures or descriptions of objects or events.

Data is often described in a data model. A data model organizes elements of data and standardizes how they relate to one another. For instance, a data model may specify that the data element representing a person be composed of a number of other elements which, in turn, represent the height and weight of the person or the color of their eyes etc. (Moody & Shanks, 1994). Data is typically designed by breaking things down into their smallest parts that are useful for representing data relationships. For example, a customer may include a list of contacts. Each contact may contain an address. Data is typically stored in logical "objects" such as a table in a database. According to The Open Group, a data object is "a passive element suitable for automated processing" (http://pubs.opengroup.org/architecture/archimate2-doc/chap04.html, accessed 2017).

For information to be gained from data, context is required. This contextual data is gained from data that describes the data that is being created, often referred to as "metadata". Often, metadata also provides data about the sensor itself or about the object or thing that is being sensed. Metadata is often defined as data about data (Bargmeyer & Gillman, 2000; Khatri & Brown, 2010). As such, we must also recognize that metadata is also data. According to Khatri & Brown (2010), metadata describes what the data is about and allows us to describe and interpret the data. As such, metadata can also be stored and managed in a database, often called a registry or repository (Bargmeyer & Gillman, 2000). Khatri & Brown (2010, p. 150) describe different types of metadata as being "physical, domain independent, domain-specific, and user metadata". These different types of metadata ensure the discovery, retrieval, collation and analysis of data. According to Khatri & Brown (2010, p. 150), physical metadata includes information about the "physical storage of data"; domain-independent metadata includes "descriptions such as the creation or modification of data and the authorization, audit and lineage information related to the data"; and user metadata includes "annotations that users may associate with data items or collections" (Khatri & Brown, 2010, p. 150).

**Definition 2.2:** Metadata is a description of a data object and the data elements stored within it.

Figure 1-4 below shows that information can be gained by combining data (from the registration of observations, measurements, decisions or transactions) with metadata (data which provides context).

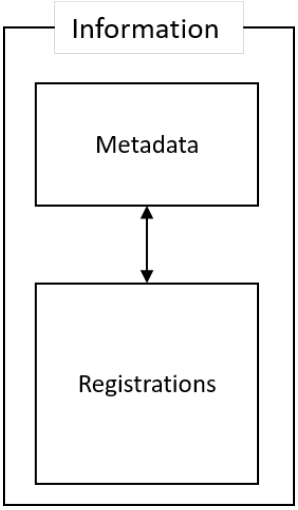


Figure 1-4: The relationship between data elements and information

In this research we follow Huang, Lee, & Wang (1999) and distinguish "information" from data by referring to information as data put in a context.

**Definition 2.3:** Information is data that has been put into context.

In practice, information is often stored within data stores such as data warehouses (Holmes et al., 2014) and visualized in the form of reports. The buildup of this information over time becomes knowledge which is also often stored digitally within knowledge management systems (Lin, 2014). The lines of responsibility may often become blurred as multiple users combine multiple data sources and data types to create multiple information products.

### 1.4.3 Asset Management Data Infrastructures (AMDIs)

Modern usage of the term "infrastructure" concerns the necessary economic and organizational foundation of a highly developed economy, especially with regards to networks of assets that are provided by the state (Buhr, 2003). Networked infrastructures are believed to be complex socio-technical systems and their complexity shows in the physical networks, and in the actor networks, as well as the combination of the two (Herder et al., 2008). Various forms of infrastructures are dealt with in Information Systems (IS) literature. Information infrastructures have been defined as "*a shared, evolving, heterogeneous installed base of information technology capabilities among a set of user communities based on open and/or standardized interfaces*" (Hanseth & Lyytinen, 2004, p. 213). Information infrastructures offer a shared resource for delivering and using information services in a community. However, this definition is insufficient with regards to data infrastructures due to the focus on information technology (IT) assets and the lack of attention for the content within the systems, the interaction of communities between themselves and with the information infrastructure itself. IT systems enable the automation of data infrastructures just as technological advances enable the development of physical infrastructures.

Another type of IS infrastructure, *Spatial Data Infrastructure* (SDI) is often used to denote to the relevant base collection of technologies, policies and institutional arrangements that facilitate the availability of and access to spatial data (Nebert, 2004). Grus et al. (2010) have shown that SDI, as CAS, evolve. The focal point of the SDI concept is facilitating the interaction between spatial data and people. A SDI can therefore be seen as a sociotechnical assembly rather than only a technical tool (de Man, 2006). SDI is an initiative intended to create an environment in which all stakeholders can co-operate with each other and interact with technology (Rajabifard & Williamson, 2001). For this research, we follow the reasoning of spatial data infrastructures and define data infrastructures as being a shared, heterogeneous, set of resources capable of evolving and therefore of being continuously able to provide data required by organizations.

**Definition 3.1:** a data infrastructure is a shared, evolving, heterogeneous, set of resources capable of providing the data and metadata required to fulfil the information requirements of organizations for their information needs.

Including the discussion on asset management organizations, we define an AMDI as shared, evolving, heterogeneous, sets of resources capable of providing the data and context required to fulfil the information requirements of asset management organizations.

**Definition 3.2:** an AMDI is a shared, evolving, heterogeneous, set of resources capable of providing the data and metadata required to fulfil the information requirements of asset management organizations.

Managing physical infrastructure assets often means balancing complex uncertainties (Volker et al., 2011). Physical infrastructure assets have long life spans, no resale value, include passive elements; are built in agile conditions, inside evolutionary, widely distributed, networked systems, and have anonymous users which are not necessarily the owners, managers or operators (Volker et al., 2011). These uncertainties are often mirrored in AMDIs. As a unique asset, data can be affected by a broad range of outside influences at indiscriminate moments in time. The end users of data are often anonymous, and the data owners often have little control over their use or production (Redman, 2008). Data also multiplies exponentially in evolutionary, networked and widely distributed systems. It is because of this that it is exceptionally difficult for asset management organizations to effectively manage their data. Data systems are complex (Redman, 2008) and many disciplines must be coordinated in order to ensure that data becomes a useful entity. Traditional information systems architecture has tended to focus on developing infrastructures that attend to specific needs and focus on specific processes.

### 1.4.4 IoT

According to Miorandi, Sicari, De Pellegrini, & Chlamtac (2012), IoT builds on three pillars, related to the ability of objects (or "things") which are 1. identifiable, 2. can communicate and 3. are able to interact, either amongst themselves or with other entities or end-users in the network. Miorandi et al. (2012) defines "smart" objects (or things) as entities that have a physical embodiment and a set of associated physical features, and which have a minimal set of communication functionalities, such as the ability to be discovered and to accept incoming messages and reply to them. Furthermore, Miorandi et al. (2012) believes that smart objects

should be associated with at least one human readable name and one computer readable address. The smart object should also possess some basic computing capabilities such as matching an incoming message to a given footprint and should also possess means to sense physical phenomena (e.g., temperature, light, electromagnetic radiation level) or to trigger actions having an effect on the physical reality (actuators).

IoT has a number of characteristics which should be born in mind when defining the scope of IoT. According to Patel & Patel (2016), a fundamental characteristic of IoT is that it displays *interconnectivity* in that things can be interconnected through communication infrastructures. Miorandi et al. (2012) describes this characteristic as ubiquitous data exchange through proximity wireless technologies. According to Miorandi et al. (2012), wireless communications technologies play a prominent role in IoT as it enables smart objects to become networked. Patel & Patel (2016) believe that IoT is capable of providing *thing-related services* within certain constraints such as privacy and semantic consistency. And Miorandi et al. (2012) considers the importance that entities in IoT can be identified and are provided with short-range wireless communications capabilities. However, as everyday objects become connected to a global information infrastructure, *scalability* issues arise at different levels (Miorandi et al., 2012). According to Patel & Patel (2016), the number of devices that need to be managed and that communicate with each other will be at least an order of magnitude larger than the devices connected to the current Internet. As such, the management of the data generated and their interpretation for application purposes is critical (Miorandi et al., 2012; Patel & Patel, 2016). This relates to semantics of data, as well as to efficient data handling. Patel & Patel (2016) believe that the devices in IoT are *heterogeneous,* being based on different technologies, and Miorandi et al. (2012) expects devices to present very different capabilities from the computational and communication standpoints. According to Patel & Patel (2016), *connectivity* enables network accessibility and compatibility, the capability of accessing and consuming data. But Miorandi et al. (2012) believes that the complexity and dynamics that many IoT scenarios will likely present calls for distributing intelligence in the system, making smart objects able to autonomously react to a wide range of different situations. Nodes in IoT may organize themselves autonomously into transient ad hoc networks, providing the basic means for sharing data and for performing coordinated tasks. As such, IoT also has the characteristic of *dynamism* as the state or number of devices changes dynamically. According to both Miorandi et al. (2012) and Patel & Patel (2016), *security* is an important aspect of IoT, and IoT

should be designed for privacy and security. Figure 1-5 below summarizes the general characteristics of IoT.

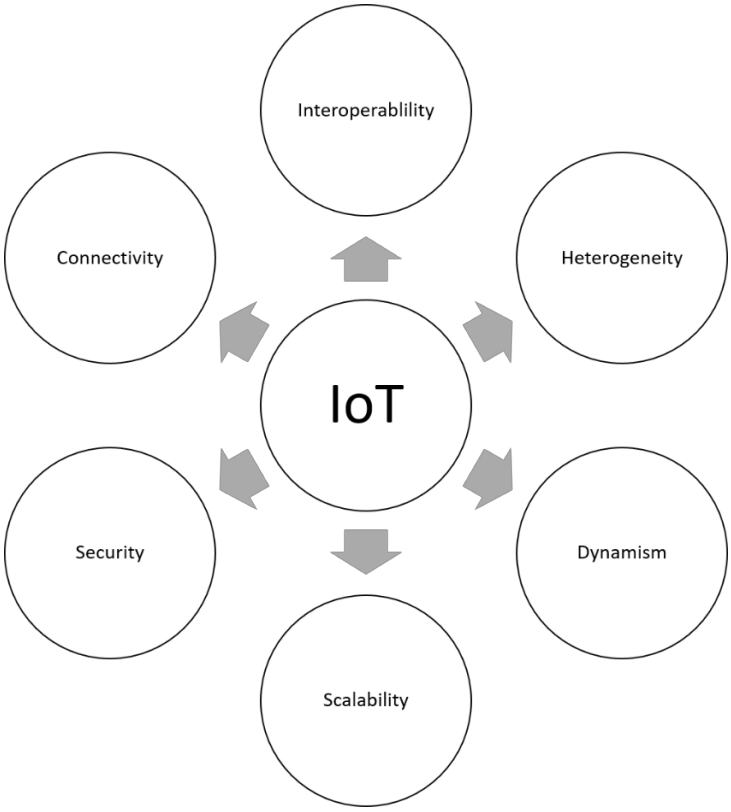


Figure 1-5: Characteristics of IoT

In this manner, IoT describes a wide range of interoperating technologies in which objects which are equipped with sensors, specifically designed software or other digital systems, are connected to the Internet and/or other networks, with a specific purpose in mind. How data is acquired, analyzed and combined into information value chains and benefits is key to IoT adoption success. As such, the true value of IoT may lay in the ways it enables to leverage entirely new sources and types of data for entirely new business models, insights, forms of engagement, way of living and societal improvements.

The term "Internet of Things" is not new, purportedly in use since 1997, and a wide variety of definitions exist. For example, Atzori et al. (2010 p. 1) define IoT as "*a network of physical objects that are able to communicate digitally over the internet*", and the Institution of Electrical

and Electronic Engineers (IEEE) have, in the past, defined IoT as "*a network of items, each embedded with sensors, which are connected to the Internet*" (IEEE, 2014 p. 6).

**Definition 4.0:** Internet of Things is a network of items, each embedded with sensors, which are connected to the Internet.

According to Xia, Yang, Wang, & Vinel (2012), IoT will increase the ubiquity of the Internet by integrating every object for interaction via embedded systems. This will enable a highly distributed network of objects communicating with human beings as well as other objects. For example, in the Netherlands, sensors installed in buoys in a countrywide network of sensors monitor the water levels in Dutch rivers and in the North Sea. The system automatically sends reports to the storm surge barriers such as the "Maeslantkering" and to their managers if water levels exceed the defined thresholds. Early predictions of rising water levels can be made and the storm surge barriers can be automatically closed to prevent major flooding. Also, utilities and independent power providers can reduce operating expenditure and cut costs associated with maintenance and labor through real-time fault monitoring capabilities provided by IoT, improving day-to-day grid effectiveness and capacity planning with detailed reporting & intelligence.

In addition, combining information from devices and other systems using expansive analysis, may provide new insights for managers of public utility infrastructure. For example, it is possible to embed wireless sensors within concrete foundation piles to ensure the quality and integrity of a structure. These sensors can provide load and event monitoring for the projects construction both during and after its completion. This data, combined with data from load monitoring sensors designed to measure weights of freight traffic, may provide managers of physical infrastructure with new insights as to the maintenance requirements of the infrastructure. According to Moreno, Santa, Zamora, & Skarmeta (2014), IoT is a vision towards a situation where "things" are provided with enough intelligence to communicate with each other without human intervention. Moreno et al. (2014) believes that the number of IoT-enabled nodes is expected to grow substantially, and as such the heterogeneous nature of implementations demands effective IoT deployments that ensure proper interoperability and reliability of network infrastructures. Ubiquitous sensing enabled by Wireless Sensor Network technologies cuts across many areas of modern day living (Gubbi, Buyya,

Marusic, & Palaniswami, 2013). Gubbi et al. (2013) believes that IoT provides the ability to measure, infer and understand environmental indicators, and the proliferation of these devices in a communicating–actuating network creates the IoT wherein sensors and actuators blend seamlessly with the environment around us, and the information is shared across platforms in order to develop a common operating picture.

IoT is an umbrella term, comprising various technologies and at the same time part of a broader technological picture. The IoT enables innovation through a combination of, amongst others, remote sensing, real-time data transport and processing, data and analytics, artificial intelligence, machine learning, cloud and edge computing, business process optimization, people, and robotics.

### 1.4.5 Data Governance

IoT data can provide new insights to help organizations face challenges, but the data must be of sufficient quality in order to be acted upon (Otto, 2013; Wende, 2007). Too much data can create "noise" which detracts van the quality of the information. A widely adopted definition of high quality data is data that is "fit-for-use" (Strong, Lee, & Wang, 1997; Wende & Otto, 2007). Using the definition provided by Strong et al. (1997), the characteristics of high-quality data have intrinsic, accessibility, contextual, and representational aspects. This also means that usefulness and usability are important aspects of quality (Dawes, 2010; Strong et al., 1997). Having data infrastructures which produce data of a quality that is aligned to the needs of the organization is therefore essential for asset management organizations which rely on data-driven decision-making processes (Al-Khouri, 2012). According to Wende & Otto (2007), companies need data quality management that combines business-driven and technical perspectives in order to respond to strategic and operational challenges demanding high-quality corporate data. As such, many organizations see data governance as a way to manage data quality (Otto, 2011b). According to Otto (2011b), the value of data depends on its quality.

According to Otto (2011b), data governance is based on the idea of data as being an organizational asset. Data governance defines mandate and responsibilities with regards to data management. As such, data governance demands binding guidelines and rules for data quality management (Otto, 2011b). Otto (2011b) therefore defines data governance as a "framework for assigning decision-related rights and duties in order to be able to adequately handle data as a company asset" (Otto, 2011b, p. 46). This suggests a simplistic causal relationship

between data governance elements. However, the variety and complexity of relationships between these and other important elements, such as ensuring compliancy to external regulations, suggests that this definition is incomplete. As such, the field of data governance remains in its infancy and many scientific sources follow the information governance definition of Weill & Ross (2004) and define data governance as "specifying the framework for decision rights and accountabilities to encourage desirable behavior in the use of data" (Khatri & Brown, 2010 p. 148). Khatri & Brown (2010) follow Weill & Ross (2004) and differentiate between "governance" and "management". According to Khatri & Brown (2010), "governance" refers to what decisions must be made to ensure effective management, whilst "management" involves making and implementing decisions. By way of example, Khatri & Brown (2010) include establishing who in the organization holds decision rights for determining standards for data quality in governance, whilst explaining that management involves determining the actual metrics employed for data quality. For example, according to Dawes (2010), stewardship demands that data be managed as a resource that has organizational, jurisdictional, or societal value across purposes and over time. As such, mature data governance processes protect data from damage, loss, or misuse, and makes information "fit for use". For example, Khatri & Brown (2010) and Dawes (2010) show that data and metadata standards govern how data elements are described, defined and represented. Khatri & Brown (2010) have developed a framework for decision domains for data governance as seen below in Figure 1-6. However, criticism for following the IT driven definition comes from Otto & Weber (2011) who believe that that data quality management is not fully comparable to IT management because of the business perspective involved. As such, data governance and IT governance are also not fully comparable. Nevertheless, Otto & Weber (2011) believe that IT governance research pursues similar objectives and although Otto & Weber's (2011) proposed contingencies (and their impact) lack validation in the context of data governance, research on contingencies influencing IT governance models may be used as starting point for the contingency research on data governance.

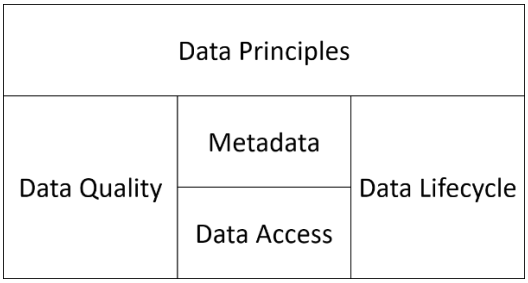


Figure 1-6: Decision Domains for Data Governance (Khatri & Brown, 2010 p. 149)

In this research we view AMDIs as CAS, and, as such, suggest that data governance provides the rules for behavior within the AMDI. In the light of these criticisms, we define data governance as specifying the framework for decision rights and accountabilities to encourage desirable behavior in the use of data (Khatri & Brown, 2010), ensures that data is aligned to the needs of the organization (Dawes, 2010), monitors and enforces compliancy to policy (Thompson et al., 2015), and ensures a common understanding of the data throughout the organization (Otto, 2011b).

**Definition 5.0:** Data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data, ensures that data is aligned to the needs of the organization, monitors and enforces compliancy to policy, and ensures a common understanding of the data throughout the organization.

### 1.4.6 Adoption of IoT

Adoption of innovations, "the decision to proceed with a full or partial implementation of an evidence-based practice" (Wisdom, Chor, Hoagwood, & Horwitz, 2014, p. 2), is a complex process. According to Wisdom et al. (2014, p. 2), understanding this process "may provide insights for the development of strategies to increase the uptake of IoT in asset management organizations". Adoption often begins with the recognition that a need exists and the decision to proceed with the implementation of the solution (Wisdom et al., 2014). However, adoption involves more than a decision to implement IoT, but also includes the staff's acceptance of the innovation (Frambach & Schillewaert, 2002). Rogers (1995), views acceptance of innovations as d*iffusion*, being a

process through which an innovation is communicated over time within a social system.

IS adoption research in other areas such as ERP (e.g. Al-Mashari, 2003; Buonanno et al., 2005; Chang, Cheung, Cheng, & Yeung, 2008) suggest that adoption of innovative technology requires intense efforts focusing on both technological and business sides of the implementation. These cases suggest that innovative technology such as IoT may structure the organization and people involved, the duality (Orlikowski, 1992) being that adopting IoT means accepting changes to processes and organizational structures, but also to people's mindsets – how they view and trust the IoT system and the data. Damanpour & Schneider (2006) have identified three phases of adoption, namely: initiation, decision to adopt and implementation. This research focuses primarily on the implementation end-state, namely a successful implementation of IoT and its acceptance within the asset management organization, but attention is also necessarily given to the process leading to acceptance of IoT.

According to Damanpour & Schneider (2006), the adoption of innovation basically means that the innovation is new to the people or organization who are adopting it. Damanpour & Schneider (2006) believe that organizations implement innovations to create change so that the unit may maintain or improve its level of performance. Therefore, we view adoption of IoT in asset management organization as IoT being new to the asset management organization and being implemented as a means of creating change in the organization so that it maintains or improves its level of performance or effectiveness.

**Definition 6.0:** Adoption of IoT in asset management organization is the new implementation and acceptance of IoT within the asset management organization as a means of creating change aimed at improving the level of performance or effectiveness of asset management.

## 1.5 Research Objective

Asset management organizations need data to achieve their business goals, but the traditional approach of providing disparate systems for each information requirement is no longer adequate Kwon et al. (2016). IoT has the potential to provide the necessary data. However, improving understanding of asset management through IoT means discovering how AMDIs are able to accommodate these new sources of data.

Data is often used for a variety of information needs in asset management processes, and asset management organizations are often data-rich environments due to the need for data to make informed decisions regarding the management and development of physical infrastructures. Data-rich asset management organizations have AMDIs. What is still unclear is what exactly an AMDI is and how it looks like. Previous research has mostly focused on either "Information Infrastructures" (Byrd & Turner, 2000; Hanseth & Lyytinen, 2004; Hanseth et al., 1996), which is generally confined to the IT capabilities of the system, or "Spatial Data Infrastructures" (Grus et al., 2010; Nebert, 2004; Rajabifard & Williamson, 2001) which is limited to infrastructures of spatial data. There has been little or no research into AMDIs, whether at organizational, regional or international levels, even though the maintenance and development of the data infrastructure shares many elements with the physical world. AMDIs are different from other information infrastructures in various ways, including:

- Asset management data have longer lifecycles than the systems that store the data.
- Users and uses are becoming invisible to the data provider.
- It is no longer clear what the exact functional and quality requirements of the data should be. The use of the data varies over time and it is hard to predict how the data will be used and what data is required.
- Data is increasingly becoming available from new, largely unregulated sources such as IoT.

What is not known is what the characteristics of an AMDI are or how the individual elements interact and behave. In order to enable asset management through IoT we need to understand the modern asset management landscape and how IoT adoption may affect this landscape.

AMDIs are complex socio-technical systems and their complexity shows in the physical networks, and in the actor networks, as well as the combination of the two (Herder et al., 2008). Data infrastructures represent information about physical reality, and as reality changes, AMDIs might also be subject to change. For example, improving understanding of asset management through IoT requires identifying potential and experienced benefits and risks of asset management through IoT.

IoT adoption can both enable and constrain asset management processes. It is assumed that IoT has much potential for asset management, however, the impact of IoT on asset management has not yet been investigated systematically and remains largely anecdotal.

Expected benefits of IoT for asset management may introduce unexpected risks (Brous & Janssen, 2015a) and, as suggested by the duality of technology (Orlikowski, 1992), IoT may become part of the structures which constrain individual actions. For example, adopting IoT for access control to public transportation may improve efficiency, but removing the human element of conductors in trains and busses may introduce unexpected risks such as increased incidences of vandalism, requiring new organizational structures to mitigate these risks. Because there is a dependence on interactions between technical and social elements, the ability to coordinate the management of data is essential to asset management through IoT. Considering the preceding discussion, our research objective is formulated as follows:

***The research objective*** is to develop a model of AMDIs that improves understanding of asset management through IoT.

As discussed above, we intend to achieve this objective through the design of a model of an AMDI that improves understanding of asset management through IoT, and facilitates communication between stakeholders in the asset management organization. To gain the knowledge required to achieve the objective and to be able to build the model, we developed five research questions to guide the research. Section 1.6 below discusses these research questions further.

## 1.6 Research Questions

To be able to design an AMDI model which accommodates IoT we desire to know what the elements are which enable a data infrastructure for asset management organizations. Traditionally, data collection, transformation and analysis processes are often done by hand but the adoption of IoT means that the data management process is becoming more and more automated. Many infrastructures are now fitted with sensors and industrial automation is becoming more accepted. IoT is influencing traditional AMDIs, forcing them to evolve in unexpected ways. From a duality perspective, asset management organizations that choose to adopt IoT should pay attention to both the adoption of technology as to the social impact this adoption causes, as IoT implementations may also bring with them unintended consequences such as the misuse of surveillance or telecom data which disregards personal privacy, or the use of sensor data which provides insight into issues other than those for which the sensor was placed in the first place. IoT might provide a variety

of benefits for asset management, but when embedded in existing structures the benefits might not be accomplished or might even result in distinct disadvantages.

IoT can benefit asset management organizations by providing enough quality data to generate the information required to help asset managers make the right decisions at the right time (Brous & Janssen, 2015b). For example, IoT can be used to collect data to determine the position and length of traffic jams, and to redirect traffic or offer alternative multi-modal forms of transport by using location sensors and analyzing traffic flow. This information can be used to provide valuable information regarding the development of road smoothness and fraying asphalt. However, IoT can also affect the asset management organization in unexpected ways. Automating processes often necessarily leads to changes to organizational structures and cultures as tasks previously performed by people become automated, whilst other tasks and responsibilities which previously did not exist become apparent (Brous & Janssen, 2015a). Furthermore, achieving the benefits of asset management through IoT also requires accounting for a variety of risks. For example, sensors might not work or might emit the wrong signals, resulting in annoyance for the public and reducing their trust in the system and damaging the reputation of the organization. This leads us to our first research question which we separate into three parts:

**RESEARCH QUESTION 1**:
How can IoT improve asset management?

1a. How can IoT be used in asset management?
1b. What are the expected benefits of asset management through IoT?
1c. What are the risks posed by asset management through IoT?

As discussed above, the objective of the research is to develop a model of AMDIs that improves understanding of asset management through IoT adoption. Achieving the research objective requires defining the scope and domain of the research. Defining AMDIs not only defines the scope of the knowledge obtained by identifying the specific domain wherein the knowledge applicable is, but also ensures that there is clarity with regards to the phenomenon under study, the AMDI. It is therefore important to define the characteristics of an AMDI. Data infrastructures represent information about physical reality. As reality changes, AMDIs

might also be subject to change. Therefore, we are interested in understanding how an AMDI is affected when faced with IoT. It is important to understand what the elements of AMDIs are. The CAS lens helps us to identify and better understand the characteristics and the behavior of AMDIs affected by IoT adoption. All real-world objects share two characteristics: they all have state and behavior (http://pubs.opengroup.org/architecture/archimate2-doc/chap02.html). For example, dogs have state (name, color, breed, hungry) and behavior (barking, fetching, wagging tail). From an asset management perspective, although perhaps seemingly more passive than dogs, bridges (for example) also have state (size, height, condition) and behavior (load-bearing, vibration etc.). Furthermore, objects can often be de-composed into smaller objects (components) which are necessarily related. Identifying the state, behavior and relationships of real-world objects is therefore important for understanding how the whole may change and develop over time. We therefore wish to know what the parts (components) of AMDIs are, but also to understand how the sum of the parts may react to the introduction of IoT. We thus arrive at our second research question which we separate into two parts and reads as follows:

**RESEARCH QUESTION 2**:
What are the elements and behaviors of AMDIs that enable asset management through IoT?

2a. What are the elements of AMDIs that enable asset management through IoT?
2b. What are the behaviors of AMDIs that enable asset management through IoT?

Once we defined the scope and boundaries of the knowledge we intend to obtain, we wish to establish a knowledge base, composed of existing findings, which builds a foundation for the research. This foundation helps guide us with the scientific contribution of the research, driven by underlying theories. Theories are important elements in designing artefacts (Pries-Heje & Baskerville, 2008), especially when used as external theories in design for the purpose of insuring that work practices and technology remain correlated and synergistic. Pries-Heje & Baskerville (2008) have identified that there are differing opinions about what constitutes design theories for information technology artefacts. For example, Walls, Widmeyer, & Sawy (1992) demonstrate that design

theories have both a product component and a development process component. Each draw upon kernel theories that enable designers to evaluate whether the product and its development process satisfy the design theory. Also, Goldkuhl (2004) specifies a need for multiple grounding of design theories, and Markus, Majchrzak, & Gasser (2002) use theories to explain the "means–ends" relationship as a practical, prescriptively causal, mechanism to justify design components. In this research we assume that the characteristics of AMDIs play important roles in the decisions made regarding IoT adoption, and at the start of the research we did not know which elements should be incorporated in an AMDI model nor what the expected behavior of AMDIs would be when adopting IoT.

We argue that an AMDI is not only a list of parts, but is a linked and complex whole. Following Miller & Page (2009), purely listing the elements of a data infrastructure would therefore reduce its complexity, meaning that AMDIs, whilst being complicated, are not necessarily complex. We argue that the coordination of dependencies between the elements of AMDIs make a significant contribution to their complexity and that AMDIs are CAS.

As CAS, AMDIs have schema which, in this research is identified within AMDIs as data governance. It is necessary to identify not only the elements of AMDIs, but also how data governance coordinates data management within AMDIs. This research shows that data governance includes several important elements, and successful data governance requires the development of a number of artefacts, but also the execution of a number of activities which ensure the proper creation, management, distribution and use of quality data. For example, ensuring that there is no confusion between a bank account and a sales account requires specific definitions of the two which are included in the business rules within the information systems and are actively managed by data stewards during discussions between the finance and sales departments. This leads us to our third research question which reads as follows:

**RESEARCH QUESTION 3**:
What are the elements of data governance in AMDIs that enable asset management through IoT?

Asset management is often conceptualized as being process-oriented (Lin et al., 2007). The asset management process itself is

complex, and involves a number of disciplines. Furthermore the asset lifecycle can span a long period of time (Steed, 1998). At every step in the process, asset management needs to collaborate with other business processes, in order to effectively manage the network (Lin et al., 2007). The cost and complexity of managing physical assets demands considerable planning to identify appropriate solutions and evaluate investment opportunities. The asset management process itself is data centric as assets need to be tracked throughout their lifecycle (Lin et al., 2007a). As such, the asset management process requires substantial amounts of data to be collected throughout all stages of a typical asset's lifecycle. This data needs to be maintained for many years to be able to identify long-term trends. The process also uses this data to plan and schedule asset maintenance, rehabilitation, and replacement activities. Ensuring the availability of the data requires the complex synergy of social and technical aspects. Ottens et al. (2006) describe socio-technical systems as including technical and social elements and their relationships. According to Ottens et al. (2006), traditional systems engineering practice tend to view social elements as being purely contextual. Ottens et al. (2006) believe that social elements should also be considered as being integral to the system. It is therefore not sufficient to only describe the technical and actor elements of the AMDI, but it is also important to include the social elements as well, and to describe the mechanisms connecting these variables. This is because designing a system is more than simply assembling the elements (Auyang, 1999). With the inclusion of social elements, the variety of relations between the elements increases considerably. There has been little research into AMDIs and models which include the technological and social aspects of AMDIs and improve our understanding of asset management through IoT are missing. This leads us to our fourth research question which reads as follows:

**RESEARCH QUESTION 4**:
What does a model of an AMDI that accommodates IoT look like?

Modelling AMDIs and the influence of data governance on their development provides insight into how AMDIs evolve when IoT is introduced so that appropriate measure may be taken to ensure that AMDIs continue to serve the goals and objectives of the asset manager. A model of AMDIs is developed within the defined boundaries of the

explanatory case studies. As will be discussed in Chapter 3, due in part to the real-time nature of the data, IoT can provide asset management organizations with many benefits such as improved forecasting, planning, reduction of costs, predictive maintenance and improved efficiency and effectiveness of reactions to events. However, these benefits are often difficult to realize as many organizations are not yet equipped to handle and interpret the data. We therefore investigate how IoT changes business processes and, as will be discussed in Chapter 2, the usability of the AMDI model. This leads us to our fifth research question which reads as follows:

**RESEARCH QUESTION 5**:
How does the AMDI model improve understanding of asset management through IoT?

To summarize, the objective of this research is to develop a model of AMDIs that improves understanding of asset management through IoT. We begin the research by defining the typical characteristics of AMDIs. Building on the relationships within the AMDI as CAS, we investigate how AMDIs adapt and evolve as IoT is adopted within the AMDI, asking what the benefits and unexpected risks of asset management through IoT may be from a duality of technology perspective. The requirements gathered whilst answering these questions lead us to understand that coordination of developments in the AMDI should take place within the scope of data governance, however, it is unclear what the principles of data governance in relation to IoT adoption are, which leads us to research question 3. Once we incorporate the principles of data governance in AMDIs into the AMDI model, we evaluate the usability of the model with test cases which occur outside of the parameters set by the exploratory case studies.

## 1.7 Outline of the Dissertation

Figure 1-7 below shows how the dissertation is structured. Chapter 2 of the dissertation goes into detail as to how the research was conducted, what methods were followed and what the underlying research philosophy is. Chapter 2 discusses the research philosophy and strategy and introduces the main artefact that is created by this research. An important section of Chapter 2 deals with the research methods followed, including the methods followed in the literature review and briefly introduces the various cases under study in this research.

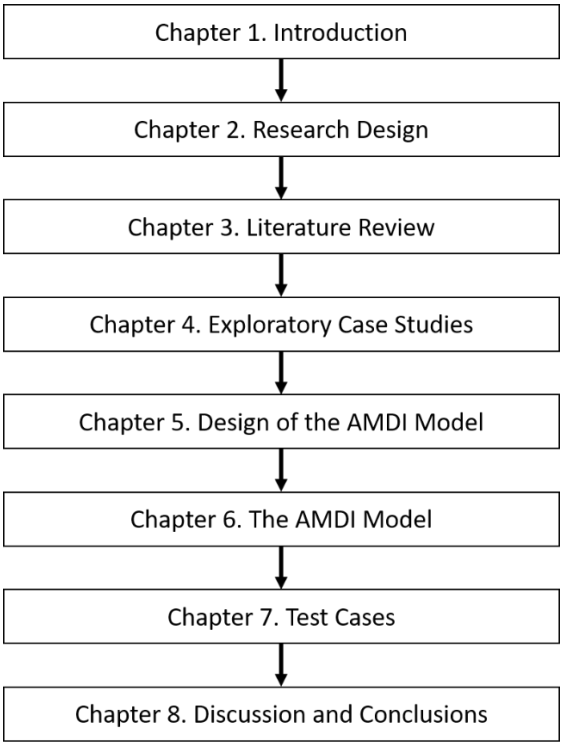


Figure 1-7: Outline of the dissertation

Chapter 3 sets the base of knowledge on which this research further builds by performing a systematic review of literature surrounding IoT adoption in AMDIs. Chapter 4 presents a discussion of the results of the exploratory case studies. The results of the literature review and the exploratory cases form the body of knowledge required to build the model of AMDIs for improving understanding of asset management through IoT, the design of which is described in Chapter 5. Chapter 6 presents a description of the model and Chapter 7 presents an evaluation of the model based on a discussion of the results of the test case studies used to evaluate the model. Chapter 8 presents conclusions to be drawn over the research, reflects on the applicability of the model and makes suggestions for further research.

# Chapter 2 Research Design

*"The fault, dear Brutus, is not in our stars,*
*But in ourselves, that we are underlings."*
**- William Shakespeare (*Julius Caesar, Act I, Scene II*)**

## 2.1 Introduction

In Chapter 1 we introduced the problem and defined a framework of research questions which guide us in achieving our objective of developing a model of AMDIs that improves understanding of asset management through IoT. We discussed the dual nature of asset management through IoT and we discussed the necessity of viewing AMDIs as CAS. In this Chapter we describe our chosen approach to answering the research questions and we describe our approach to designing a model of AMDIs.

The accommodation of IoT in AMDIs can be seen as a "wicked" or ill-structured problem (Checkland, 1981; Simon, 1973) as, while AMDIs can appear durable for a time, they are constantly evolving and adapting to changing social needs. Furthermore, simply implementing IoT in asset management does not necessarily lead to its acceptance by asset managers (Can Duzgun, 2017; Spiegeler, 2017). Ill-structured problems have various problem components such as varying stakeholders and organizational, technological, and content components. In addition, the "solution" may often lie in different places such as business rules, network structures or technologies, and different solutions may also be required at different times. For example, infrastructures appear stable only when oppositional tendencies are brought into proximity through reflection or interaction (Ford & Backoff, 1988; Tilson, Lyytinen, & Sorensen, 2010). This requires involving a variety of contradictory elements, and there is often a temptation to simplify the truth which may conceal complex interrelationships. To avoid this temptation, it is necessary to follow a disciplined strategy and to be guided by a defined research philosophy. In the following section, section 2.2, we discuss our research philosophy and the approach used in this research. In section 2.3 we discuss the literature review methodology and in section 2.4 we discuss the case study methodology. Section 2.5 summarizes the chapter.

## 2.2 Research Philosophy and Approach

This research has been conducted from a constructivist perspective which advocates that knowledge is constructed in the mind of the learner (Bodner, 1986). In other words, learners construct understanding and look for meaning, trying to find regularity and order in the events of the world even in the absence of complete information (Watzlawick, 1980). The reason for choosing the constructivist philosophy is because IoT technology is relatively new, and IoT has not yet been widely adopted by asset management organizations. As such, all cases of asset management through IoT have included an adoption period wherein the adopting organization has been forced by means of trial and error to learn the best-fit methods. Furthermore, this research also follows the design science paradigm in which the researcher takes an active part in the investigation by creating an artefact which itself may influence the research environment. During the design phase of the research, the researcher is forced to construct understanding and look for meaning in the cases, often in the absence of complete information. As such, we argue that the constructivist perspective is valid as not only are asset managers themselves forced by the disrupting technology of IoT which is in constant development to actively develop and learn from the world around them in order to be able to achieve their goals, but the design paradigm of the research also requires the researcher to construct knowledge.

To avoid simplifying complex interrelationships within AMDIs, we were forced to seek a good enough solution based on maintaining equilibrium around acceptable conditions. Simon (1996) refers to this search for solutions as "satisficing", settling for choices that satisfy the problem definition at a certain point in time. It is therefore important that problem-solving processes be implemented so that the best possible solution is achieved within pre-established limits. With this in mind, information infrastructures researchers have increasingly adopted the design science research approach to understand and solve ill-structured problems within the information systems research domain (Hevner & Chatterjee, 2010). Utilizing design science within this research provided us with a scientific research framework for structuring the AMDI by investigation, proscribing a "satisficing" solution and evaluating this solution.

Design science focuses on rigorously building and examining artefacts that serve human purposes (March & Smith, 1995). Building and assessing artefacts is the core of design science (Hevner, March, Park, & Ram, 2004; Orlikowski & Iacono, 2001). Design science is technology-oriented and artefacts are assessed against criteria of utility and value

(March & Smith, 1995). An artefact is something that is "artificial", or in other words, constructed by humans, as opposed to occurring naturally (Simon, 1996). Nevertheless, for the purposes of design science, the artefact must have some purpose. Utility is important in that the artefact must be designed to solve a specific problem and in this manner, advance knowledge. This requires building knowledge about the environment within which the artefact is being used as fulfilment of a purpose or adaptation to a goal involves a relation between the purpose, the character of the artefact and the environment in which the artefact performs (Simon, 1996).

The problem this research is attempting to "satisfice" is improving the understanding of asset management through IoT. The artefact created in the research is the model of AMDIs. We therefore define our design objective as follows:

***The design objective*** of this research is to develop a model of AMDIs which accommodates IoT.

The model of the AMDI satisfices the problem by describing how AMDIs can accommodate IoT, improving understanding of asset management though IoT and providing insights for asset managers into the expected benefits and related risks of asset management through IoT. We follow the framework of (Hevner et al., 2004) who have articulated a research framework centered on designing and building innovative IT artefacts. This framework, illustrated in Figure 2-1 below, demonstrates that the environment, knowledge base and evaluation of the artefact surround and connect with the development of the artefact.

Figure 2-1 shows there are three interdependent issues which are addressed by adhering to three research cycles. The three interdependent issues are: the environment, the design research (or the development of the artefact), and the knowledge base. The three cycles which connect these issues are: the relevance cycle, the design cycle, and the rigor cycle.

The rigor cycle develops the research project by providing past knowledge to ensure its innovation (Hevner, 2007). Whilst the relevance cycle is more concerned with utility, the rigor cycle focusses on truth. It is the rigor cycle of design science that separates design science from design practice. According to Hevner (2007), research rigor in design science is achieved by the researcher's selection and application of the appropriate theories and methods for constructing and evaluating the

artefact. This is embodied within the research in the form of the knowledge base.

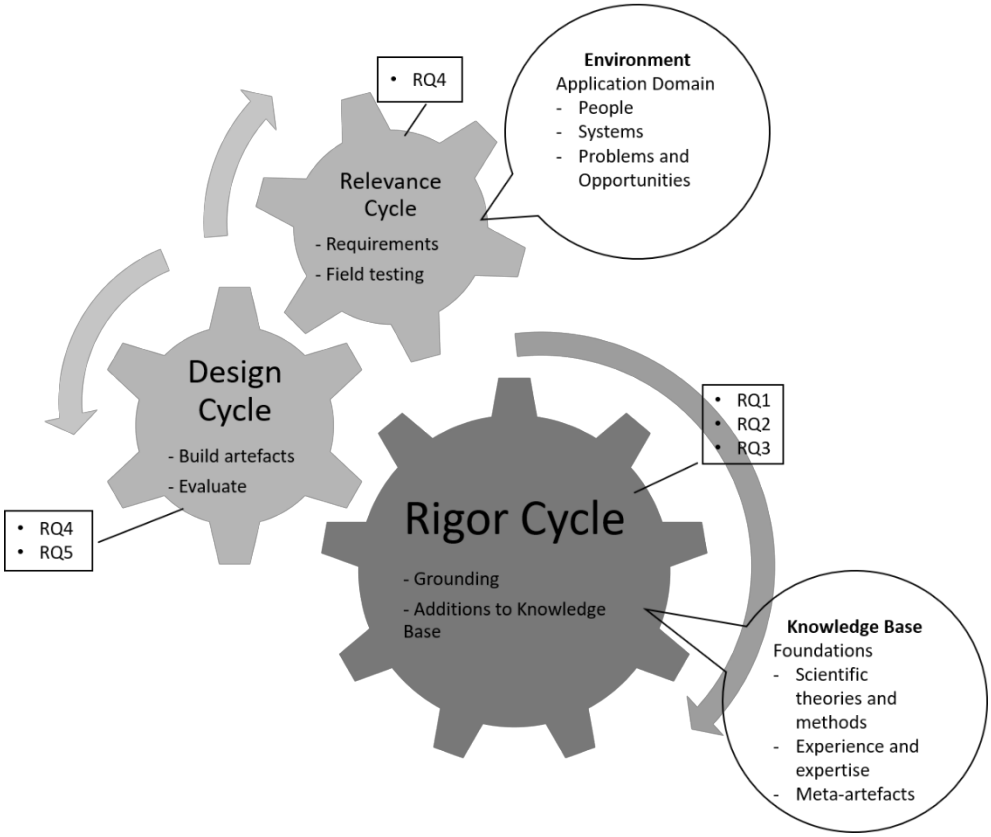


Figure 2-1: Design Science Research Cycles (Hevner, 2007)

According to Simon (1996), design science research desires to improve the environment by introducing new and innovative artefacts and the processes for building these artefacts. The relevance cycle ensures *utility* of the artefact. Therefore, design science research often begins "by identifying and representing opportunities and problems in an actual application environment" (Hevner & Chatterjee, 2010 p. 17). In this research the rigor cycle is embodied by the definitions and drivers described in Chapter 1, the research design (Chapter2) and the literature review (Chapter 3). The literature review, together with the definitions and drivers builds the scientific platform on which this research is based and discusses the scientific state of the art, whilst the exploratory case studies explore the current experience and expertise of asset management organizations.

The relevance cycle provides the requirements as inputs, and defines the acceptance criteria for testing the results. It is therefore important within the relevance cycle to ensure familiarity of the environment within which the research takes place. The *environment* defines the problem space (Simon, 1996) and refers to people, organizations and their technologies and infrastructures. This research investigates the impact of IoT on asset management. The environment of asset management, the asset management organization, is an integral part of the AMDI. This means that we need to thoroughly describe the environment, the asset management organization, in order to place this research in context, define the scope of the research and identify the utility of the research as well as identify the acceptance criteria. As such, the relevance cycle is embodied in this research by the *requirements* gathered during the literature review (Chapter 3) and the exploratory case studies (Chapter 4).

The central Design Cycle iterates between the building and testing the design artefacts. The artefact created by the research is a model of AMDIs that accommodates IoT. The model is described in Chapter 6 and is built based on the requirements gathered during the relevance cycle. The model is evaluated by means of test case studies in Chapter 7.

## 2.3 Literature Review Methodology

Following Webster & Watson (2002), the literature review was developed concept centrally. During the reading phase, we compiled a matrix of concepts into which the literature was grouped. According to Denyer & Tranfield (2009), the aim of analysis of literature is to break down individual studies into constituent parts. An important purpose behind this activity being to analyze consistency of interpretation and definitions (Webster & Watson, 2002). We therefore followed the recommendations of Wallace & Wray (2016), Kitchenham (2004) and Denyer & Tranfield (2009) and collated the literature according to a series of questions as listed below:

- What are the general details of the study?
- What type of study is this?
- What are the broad aims of the study?
- In which context was the study conducted?
- What are the key findings?

Context is important in a systematic review (Denyer & Tranfield, 2009) so we grouped the key concepts of AMDIs according to focus areas identified within the broad aims of the study. In the literature, theoretical precepts

are often discussed, but there are few systematic accounts of the adoption of IoT in AMDIs in practice or how these concepts emerge, or what the implication of adopting these concepts may be. Therefore, the second step was to conduct explorative case studies to gain a deeper understanding of the manifestation of AMDIs in a real world, public utility infrastructure, asset management through IoT setting.

## 2.4 Case Study Research

More and more, the attention of information systems researchers has been drawn to social issues associated with the development and use of technology (Darke, Shanks, & Broadbent, 1998). As previously discussed, AMDIs are highly complex due to the social nature of the phenomenon. The design of data infrastructures in asset management organizations is too complex to emulate in an artificial setting and to study using objective research instruments. The research therefore uses case study research which is a qualitative research method particularly suited to researching contemporary phenomena that cannot be separated from the environment they are embedded in (unlike laboratory experiments, for example) and that have not been scientifically studied to a large extent so far (Benbasat, Goldstein, & Mead, 1987; Yin, 2009). Case study research is a widely used qualitative research method in information systems research, and is well suited to understanding the interactions between information technology-related innovations and organizational contexts (Orlikowski & Baroudi, 1991).

The research design follows the case study methodology proposed by Yin (2009). According to Yin (2009), the design of case study research includes:

- the research questions
- the unit of analysis
- the propositions for research
- the logic which links the data to the propositions
- the criteria for interpreting the findings.

It is not only generalization that presents challenges when adopting the case study methodology; the reliability aspect should also be taken into consideration. Reliability refers to the demonstration that the operation of a study, such as the data collection procedures, can be repeated with the same results (Yin, 2009). Yin (2009) recommends employing a well thought out research protocol to ensure reliability. According to Yin (2009), a case study protocol is a formal document which describes the set of procedures involved in the collection of data for a case study. The

protocol used in this research follows the advice from Yin (2009) and includes the problem statement, a delineation of the unit of analysis, the steps (including the altering of the steps) to be taken, the procedures for contacting key informants and making field work arrangements, reminders for implementing and enforcing the rules for protecting the privacy of human subjects, a detailed line of questions, and a preliminary outline for the final case study report.

### 2.4.1 Answering the Research Questions

The research necessarily seeks to answer the research questions as discussed and defined in Chapter 1. As such, we do not discuss these further in this section. However, we do wish to explain where and how the research answers the questions posed. Figure 2-2 below shows how the research was phased to include the three research cycles of Design Science.


Figure 2-2: The phases and design science cycles of this research

As depicted in Figure 2-2, the research followed 5 phases through the 3 design science cycles. Phase 1 made up the research design. Phase 2 and 3 included the literature review and exploratory case studies respectively. Phases 2 and 3 were completed iteratively, as suggested by the Design Science paradigm, in the form of cycles in which the literature review and exploratory case studies completed the answers to Research Questions 1, 2, and 3. As such, the exploratory case studies are driven by Research Questions 1, 2, and 3 which serve to provide input for the requirements of the AMDI that enables IoT adoption.

Answering the first three research questions provided us with the requirements needed to develop the design propositions and design principles which drive the AMDI model design which was created during Phase 4. The design and build of the AMDI model formed the answer to Research Question 4 which asks what an AMDI looks like. Research Question 5 asks if the developed AMDI model improves understanding of

asset management through IoT, and this question is answered in phase 5 of the research which tests the model by means of explanatory test cases.

### 2.4.2 Unit of Analysis and Case Selection

The phenomenon under study is the development of AMDIs which accommodate IoT. AMDIs can occur at many levels and therefore it is important to define the unit of analysis of this research. There have been a good number of initiatives at international level, such as the Infrastructure for Spatial Information in the European Community (INSPIRE), at the national level, such as the National Spatial Data Infrastructure of the United States, and at the inter-organizational level, such as the Maritime Single Window initiative. However, despite these initiatives, little attention has been given to AMDIs within the participating organizations themselves. Data is created within organizations, mostly to fulfil the needs of the organization itself, not external users. AMDIs operating above the organizational level are forced to rely upon the goodwill of the participating organizations whereas AMDIs within the organization serve a distinct and definable purpose. Based on the research questions, we therefore define the unit of analysis as *AMDIs within asset management organizations*.

Whilst the literature review provides us with a base of theoretical knowledge, it is important to gain a deeper understanding of the AMDIs in real-world cases in which the boundaries of the case are well defined (Yin, 2009). The next step in the design of the case study is therefore the choice of cases. Whilst single cases are recommended where the case represents a critical test of existing theory, or where the case is a unique event, or where the case serves a revelatory purpose, a limited number of case studies may be more successful with regards to theory formulation and testing (Yin, 2009). Using more than one case study provides us with the opportunity to build the theory irrespective of an organization, which improves the argument for generalization. The evidence from multiple cases is often considered more compelling and the research more robust (Herriott & Firestone, 1983). We therefore decided to employ multiple case studies for this research. Each case is selected so that it predicts similar results through literal replication. The cases selected in this research all have asset management as their primary process. Within this research, we initially assumed that there are more than one asset management organization and those organizations face similar challenges.

Concerning the number of cases to be studied, we were necessarily limited by the constraints of time and budget, but a minimum number of

cases was considered crucial to ensure validity. Since the multiple-case studies approach does not rely on representative sampling logic, the typical criteria regarding sample size was deemed to be irrelevant (Yin, 2009). Instead, sample size was determined by the number of cases required to reach saturation, that is, data collection until no significant new findings are revealed (Patton, 2002). The cases were selected to encompass instances in which IoT adoption in AMDIs are likely to be found. As such, we focused on organizations that are tasked with maintaining infrastructure which has major significance to Dutch society.

A number of variables which may affect how asset management organizations adopt IoT in asset management were identified at the start of the research:

- Culture
- Organization type: Public or Private?
- Organization type: is it an asset management organization?
- Organizational size
- Geographical coverage of the infrastructure network
- Asset management domain

According to Wisdom et al. (2014), as adopting organizations operate within their contexts and outside environments, socio-political factors can influence adoption of innovative technologies. Therefore, culture and organizational type were considered to be factors affecting asset management through IoT. Theoretical models of user behavior are not universally applicable because each country has its own unique cultural characteristics (Hsu, Tien, Lin, & Chang, 2015). Furthermore, Wisdom et al. (2014) believe that external policy and regulation may be positively associated with adoption of new technologies (e.g. Aarons, Hurlburt, & Horwitz, 2011). As such, we took steps to ensure internal validity by avoiding cultural and legal variations through investigating only not-for-profit (government or semi-government) organizations in the Netherlands.

The variables originate from the assumption that actions are needed at sectorial level. According to Trequattrini, Shams, Lardo, & Lombardi (2016), although regulations regarding the introduction and governance of the AMDI are important, self-regulation should also not be underestimated. With regards to defining the extent of the domain within which the results of the research remain valid, we determined that the cases should be taken from varying sub-domains within the asset management sector as well as from varying levels of geographic coverage of the infrastructure network being managed. We did this to ensure diversity and external validity through replication logic (Eisenhardt, 1989;

Yin, 2009), in which each case serves as a distinct experiment that stands on its own as an analytic unit. The sub-domains of the asset management sector were surface water management, ground water management, road management and electricity management. The levels selected were the national, regional and local levels respectively. Three organizations tasked with maintaining their nation's infrastructure was determined to be the minimum required to achieve saturation.

Any use of multiple-case designs should follow replication logic to guarantee external validity. For this reason, we defined the following criteria which were used to select the different cases defined in Table 2-1 below:

Table 2-1: Criteria used to define the case selection

| Number | Criteria | Reason for Criteria |
|---|---|---|
| 1. | The case must occur within a distinct organization. | Construct validity: Unit of Analysis is at the organizational level |
| 2. | The primary processes of the organization must be focused on the management of significant infrastructure. | Construct validity: Unit of Analysis is encompassed by the asset management domain dealing with significant infrastructure assets. |
| 3. | The case environment should be "data-rich". This means that the organization should produce, manage and maintain at least 5 large datasets as well as a more than twenty small to medium data sets which support the asset management process. | Construct validity: Unit of analysis is the AMDI and thus needs to be present within the organization. |
| 4. | The AMDI must include at least one example of IoT adoption. | Construct validity: Phenomena under study is the enablement of IoT adoption in AMDIs and thus IoT adoption needs to be present within the organization. |
| 5. | The case should occur within The Netherlands. | Internal validity: Literal replication to deal with possible confounding influences of culture. |
| 6. | The organization should be of type government or semi-government (majority shareholders should be government). | Internal validity: Literal replication to deal with possible confounding influences brought about by commercial interests. |

| Number | Criteria | Reason for Criteria |
|---|---|---|
| 7. | Cases should occur at varying geographic coverage levels. | External validity: Theoretical replication to define the domain to which the findings of the study can be generalized – are the results valid for all levels? |
| 8. | Cases should occur in varying asset management domains. | External validity: Theoretical replication to define the domain to which the findings of the study can be generalized – are the results valid throughout the asset management domain? |
| 9. | The organization must be willing to cooperate with researchers and must be willing to provide access to the information required for the research. | Reliability: The research must feasibly be carried out and should be repeatable. |

The initial case studies were of an exploratory nature, in other words, they aim at laying the foundation for pertinent hypotheses or propositions for further inquiry. The exploratory cases selected were all located in The Netherlands, within the context of asset management concerning infrastructure in the water management domain. The case that was chosen at the national level was the automatic measurement of hydrological data in Dutch Waters, "Landelijk Meetnet Water", (LMW), a mission critical data infrastructure for the management of Dutch waterways. The case chosen at the regional level was the Decision Support System for Main Pumping Stations (BOS), a mission critical system for the management of main pumping stations at the Delfland Water Authority. The case chosen at the local level was the automatic monitoring of ground water levels in the Municipality of Rotterdam. Gauges have been placed in throughout the Rotterdam polders to constantly measure the groundwater levels. Table 2-2 below presents an overview of the cases chosen.

Table 2-2: Explorative case overview

| Case Number | Case Study Name | Organization | Level | Organization Type | Domain |
|---|---|---|---|---|---|
| 1. | National Water Measurement Network | Rijkswaterstaat | National | Central government | Surface Water management |
| 2. | BOS | Water Authority Delfland | Regional | Regional government | Surface Water management |

| Case Number | Case Study Name | Organization | Level | Organization Type | Domain |
|---|---|---|---|---|---|
| 3. | Ground Water Measurement | Municipality of Rotterdam | Local | Local government | Ground Water management |

We needed to be able to assess the model in environments other than those defined in the exploratory case criteria. In the first test case at the national level, we studied a use case within the same organization as the first exploratory case, however, in a different asset management domain. In this case, we wished to investigate whether the model remained valid for domains other than water management. Our first test case was the automatic measurement of the weight of vehicles over the Dutch National Highways, "Weigh-In-Motion" (WIM), occurring in the domain, road management. In our second and third test cases at the regional and local level, we also wished to investigate whether the model remained valid in organizations other than government organizations. We therefore chose uses cases within a utilities company, Stedin. Our second test case (case 5) is Smart Meters, a smart energy system test. The third test case (case 6) is that of Hoog Dalem, smart management of energy in a local setting. Table 2-3 shows an overview of the test cases chosen.

Table 2-3: Overview of the Test Cases

| Case Number | Case Study Name | Organization | Level | Organization Type | Domain |
|---|---|---|---|---|---|
| 4. | Weigh-In-Motion | Rijkswaterstaat | National | Central government | Road management |
| 5. | Smart Meters | Stedin | Regional | Regulated Industry | Energy management |
| 6. | Hoog Dalem | Stedin | Local | Regulated Industry | Energy management |

### 2.4.3 Developing the Propositions

In exploratory cases, Yin (2009) concedes that no elaborated propositions can be specified beforehand (in contrast to descriptive and explanatory case studies). Nevertheless, Yin (2009) stipulates that case studies be purpose-oriented, in other words, that there has to be a preliminary conceptual framework guiding the exploration. This research uses Duality

of Technology (Orlikowski, 1992) and CAS as preliminary conceptual frameworks to guide the exploration, assuming that AMDIs are CAS and that management organizations initiate asset management through IoT in order to achieve expected benefits. Due to the limited amount of scientific knowledge regarding AMDIs, the initial case studies were of an exploratory nature, aimed at laying the foundation for propositions used to develop the AMDI model.

The results of the literature review and exploratory case studies provided the requirements for the development of the design propositions in the following way. In answer to research question 1, duality of technology was used as a guiding framework to determine the perspective used to describe the AMDI. From this perspective, the exploratory cases were analyzed and stakeholder requirements which improve understanding of asset management through IoT were listed.

Next, CAS theory was used as a guiding framework to determine the perspectives used to describe the functional elements and behavioral behaviors of the AMDI. From these perspectives, the exploratory cases were analyzed and requirements which deal with the elements and behaviors of the AMDIs were listed.

Once the requirements of the AMDI model were known, design propositions were derived based on the need to improve understanding of asset management through IoT. The requirements and the design propositions formed the basis for the design principles which drive the design of the AMDI model and which are tested within the test case studies which are of an explanatory nature.

### 2.4.4 The Logic Linking the Data to the Propositions

Triangulation of uses of IoT in AMDIs found within the literature with those found in the cases was made by listing the uses of IoT found in literature and comparing these to the uses of IoT exposed in the interviews and internal documentation. Duality of technology (Orlikowski, 1992) was used to drive the initial views of the exploratory cases, directing the development of stakeholder requirements which focus on the use of IoT to improve asset management. There were several iterations throughout the research as the literature and cases introduced new uses of IoT in asset management. When researchers take an explorative approach, they start with a set of observations and then they move from those experiences to a more general set of propositions about those experiences. Therefore, due to the inherently explorative approach to the initial stage of the research, the “requirements” phase of the relevance cycle, we began by collecting data relevant to the impact of IoT on AMDIs.

Similarly to the development of requirements regarding uses of IoT in asset management, the characteristics of data infrastructures as CAS found in literature were listed and compared with the evidence of data infrastructure characteristics pertaining to IoT adoption found in the case study analysis. There were several iterations throughout the research as the literature and cases introduced new data infrastructure characteristics. Triangulation of characteristics of AMDIs found within the literature was made by listing AMDI characteristics found in internal documentation and comparing these to the AMDI characteristics exposed by the interviews.

Once a substantial amount of data had been collected, we stepped back to get a bird's eye view of the data. At that stage, we looked for patterns in the data, and iteratively began developing our theory to explain the patterns. We did this by listing the elements and behaviors of AMDIs according to the relevant asset management processes to get a sense of how AMDIs are affected by IoT adoption. In this way, we determined the requirements of an AMDI that improves understanding of asset management through IoT adoption.

Following this process also allowed us to iteratively identify the functional elements of AMDIs and link them to the uses of IoT in asset management. Linking the functional elements of AMDIs to the uses of IoT in asset management led us to the development of the design propositions.

The design propositions (together with the requirements) form the basis for the design principles of the AMDI model and are considered in this research to be the propositions driving the test case studies.

Table 2-4 below summarizes the logic linking the data with the propositions associated with each research question.

Table 2-4: The logic linking the data with the propositions associated with each research question

| **Propositions** | **Logic** |
|---|---|
| Propositions related to research question 1 | Triangulation of uses of IoT in AMDIs found within the literature with those found in the cases was made by listing the uses of IoT found in literature and comparing these to the uses of IoT exposed in the interviews and internal documentation. |

| Propositions | Logic |
|---|---|
| Propositions related to research question 2 | Triangulation of elements and behaviors of AMDIs found within the literature was made by listing AMDI characteristics found in internal documentation and comparing these to the AMDI characteristics exposed in the interviews. |
| Propositions related to research question 3 | Triangulation of characteristics of data governance in AMDIs found within the literature was made by listing data governance characteristics found in internal documentation and comparing these to the data governance characteristics exposed in the interviews. |
| Propositions related to research questions 4 and 5 | Pattern matching by listing the agents, data and technology of AMDIs according to the relevant asset management processes.<br>Pattern matching by describing the environments of AMDIs and how they affect the development of the AMDI.<br>Pattern matching by listing the data governance of AMDIs according to the relevant asset management processes.<br>Pattern matching by listing the behaviors of AMDIs according to the relevant asset management processes. |

### 2.4.5 The Criteria for Interpreting the Findings

In design science, it is important that a distinction is made between the empirical part and the design part of the research (March & Smith, 1995). According to March & Smith (1995), the design sciences are assumed to be able to add to, or replace, an existing part of reality. This means that although attention must be paid to the internal consistency of the research, "external validity" cannot be fully stated in advance of practical application. Instead, March & Smith (1995) believe that external validity may be achieved after implementation by assessing the design, the criteria being whether the implementation works according to pre-established specifications, and whether there is an improvement in comparison to the previous situation. Also, this research follows the case study methodology as outlined by Yin (2009), and when doing case studies an important strategy for interpreting findings is to identify and address rival explanations. Addressing such rivals becomes a criterion for interpreting the findings. We therefore focus on three main tests in this

research. First, we examine the validity of the case studies for investigating the phenomena of asset management through IoT. Second, this research seeks to develop a model of AMDIs which improves understanding of asset management through IoT adoption and, as such, we also wish to test the usability of the model. Third, we test the design propositions.

*Test 1:*
The validity test of the case studies, test 1, is performed on all the case studies on the basis of the criteria for case selection outlined in section 2.4.2 above.

*Test 2:*
Following (Bots & Sol, 1987), evaluation of the model through test case studies suffices to test the usability of the model. In this research we follow Rubin & Chisnell (2008, p. 4) and define usability as "*the absence of frustration in using it*". In other words, "*the user can do what he or she wants to in the way that he or she wants to do it, without hindrance, hesitation or questions*" (Rubin & Chisnell, 2008, p.4). Rubin & Chisnell (2008) suggest that "usefulness", "effectiveness", "efficiency", "learnability" and "satisfaction" are important criteria when evaluating a product. The criteria we have defined to determine the usability of the model for enhancing our understanding of asset management through IoT and improving communication of the system details between stakeholders follow the recommendations of Rubin & Chisnell (2008), and are defined in Table 2-5 below.

Table 2-5: Criteria for testing the usability of the model.

| Number | Criteria | Reason for Criteria |
|---|---|---|
| 1. | Each part of the model should be filled for the specific case. | Construct validity:<br>Effectiveness – all necessary parts of the AMDI should be present otherwise the model is overcomplicated. |
| 2. | All parts of the AMDI for the specific case should fit into the model. | Construct validity:<br>Effectiveness - if parts of the infrastructure exist which do not logically fit into the model than the model is incomplete. |

| Number | Criteria | Reason for Criteria |
|---|---|---|
| 3. | The user should be able to read and understand the entire model within the time limits of a two hour workshop. | Internal validity:<br>Efficiency - the user should be able to map out the system using the model in a reasonable amount of time. |
| 4. | The user should be able to work with the model after a short explanation lasting no more than 15 minutes. | Internal validity:<br>Learnability - the user should be able to use the model easily with minimal time and effort needed to learn to use the model. |
| 5. | The words used to describe the model by the user should be generally positive. | Internal validity:<br>Satisfaction - the user's perceptions, feelings and opinions of the model should be positive. |

As the goal is to improve understanding of asset management through IoT, attention is given in the case studies to the asset management process before IoT adoption. Traditional asset management processes are described and compared with asset management processes after implementation. Therefore, with regards to our third test, the criteria for testing the design propositions rests on how IoT has changed asset management processes in the cases with regards to the following possible rival explanations which were identified during the design phase of the research:

- Technical differences
- Organizational differences
- People differences

Our model is intended to improve understanding of asset management through IoT. We therefore investigate what is required in order for asset management through IoT to be successful, describing the elements and behaviors of AMDIs and describing the schema of AMDIs (which is interpreted as data governance). These elements, behaviors and characteristics provide the input required to build the model of the AMDI which accommodates IoT.

*Test 3:*
The aim is to develop a model of an AMDI which improves understanding of asset management through IoT. As such the criteria for interpreting the results of the test cases and determining the success of the model in improving understanding of asset management through IoT rests on an examination of the proofs of the design propositions as described in Chapter 5 and discussed in the test case study results (see Chapter 7) with regards to possible "craft" and "real-world" rivals as suggested by Yin (2009, p. 141). These criteria are outlined in detail in Chapter 7.

## 2.5 Reflections on the Research Design

We seek to improve understanding of asset management through IoT. The research aims to achieve this objective by describing a model of AMDIs which accommodates IoT adoption. The model is meant to enhance our understanding of asset management through IoT and facilitate communication between stakeholders. This research is conducted from a constructivist perspective as all cases of IoT adoption in asset management have included an adoption period wherein the adopting organization has been forced by means of trial and error to learn the best-fit adoption methods. "Improving" means making something better, and so we also make the conscious choice of using the design science philosophy, with the goal of achieving a satisfactory result. Another principal choice is the use of case studies as the research method.

The choices of philosophy, approach and methodology have inherent limitations which means that there are threats to the validity of the results as well as restrictions on statistical generalization which also means that we must rely on analytical generalization. To gain an overview of how IoT affects asset management, we need to identify the various characteristics of AMDIs. We conduct an extensive literature review and perform three explorative case studies utilizing a variety of instruments to collect primary and secondary data. The literature review and explorative cases provide the design requirements for building a model of an AMDI which accommodates IoT. We then evaluate the validity and generalizability of our model, whether our model improves understanding of asset management though IoT by means of explanatory test case studies.

Constructivism is often criticized due to its tendency towards epistemological relativism (Liu & Matthews, 2005). To avoid giving a one-sided, biased representation of this study's findings and to deal with the criticisms on constructivist research, various measures are taken by the

researcher. First, different perspectives were examined. For instance, we not only focused our literature review on the identification of uses and benefits of IoT in asset management, but also on the risks that adoption of IoT brings to asset management. Furthermore, we interviewed people working in asset management from different levels of the organization, including the strategic, tactical and operational levels, and we employed multiple data gathering techniques. In order to counteract the impact of epistemological relativism, we included case studies from organizations working at different levels, namely national, regional and local, and from different domains, namely, water management, road management and energy management. Furthermore, the exploratory case studies were conducted over a period of 18 months which helped insure that the results depicted more than a "snapshot in time".

Second, the process that led from data gathering to findings and conclusions was made as transparent as possible, and various measures were taken to allow for future replication of the study so that further generalizations are made possible. For example, a case study protocol was developed for the elicitation of AMDI requirements in the exploratory case studies and for the testing of the model in the test cases. Furthermore, implementation guidelines were developed in order to provide asset managers in the test cases with concrete implementation methods of the model. In the interviews, both arguments for and against adoption of IoT were identified and described. We tried to reduce the researcher bias by involving multiple interviewers and including group workshops with external observers who had not been involved in the research before.

In order to ensure representativeness, validity and generalization of results, this research employs a multiple case study approach with numerous sources of evidence through replication logic. Three exploratory case studies are explored over a period of two years to identify AMDI requirements. The cases were selected to reflect multiple levels of organizations within a physical asset management domain. Multiple data capture methods were utilized in order to effectuate triangulation of results and in all cases the researcher was given wide-ranging access to documentation and personnel. Three test cases are selected which occur in different asset management areas to those investigated in the exploratory cases.

# Chapter 3 Literature Review

*"He reads much; he is a great observer,*
*and he looks quite through the deeds of men."*
**- William Shakespeare (Julius Caesar: Act-I, Scene-II)**

## 3.1 Introduction

In Chapter 2 we described our approach to answering the research questions. The research questions guide us in confirming the dual nature of IoT and the necessity of viewing AMDIs as CAS so that we may be able to develop a model of AMDIs which improves understanding of asset management through IoT. In Chapter 3 we seek to develop a knowledge base of asset management through IoT on which we can build. This Chapter therefore takes the form of a systematic literature review.

According to Webster & Watson (2002), a methodological review of past literature is important for any academic research, and they criticize the Information Systems (IS) field for having very few theories and outlets for quality literature review. A lack of proper literature reviews has hindered theoretical and conceptual progress in information systems research (Levy & Ellis, 2006; Webster & Watson, 2002). This literature review therefore follows the method proposed by Webster & Watson (2002) and Kitchenham (2004), as described in Chapter 2 and attempts to systematically analyze and synthesize literature and advance the knowledge base of AMDI research. Our research objective is to develop a model of AMDIs that improves understanding of asset management through IoT. We therefore need to understand how asset management can be affected by IoT adoption – what are the benefits, and what are the risks of asset management through IoT? There is only limited research on AMDIs, and models for improving understanding of asset management through IoT are missing. Therefore, we aim to improve understanding of asset management through IoT by describing a model of AMDIs which can accommodate IoT adoption. We also need to understand what the characteristics of AMDIs are, and how they may be modelled. This we need to do in order to be able to model the coordination of the various elements contributing to successful asset management through IoT through means of data governance. As such, the literature review also

serves to help us understand what data governance in an asset management setting entails.

## 3.2 Methodology

Asset managers are increasingly looking to adopt IoT to automate public utility infrastructure asset management processes and provide the data required for data-driven decision-making. But although more and more data is becoming available through IoT, not all organizations are equipped to handle this data. IoT data is collected, stored and analyzed within data infrastructures, but adoption of IoT in asset management is a difficult and complex process and expected benefits are often not achieved. Therefore, a main objective of this literature review is to learn and understand how IoT may affect asset management – what are the potential benefits and risks to asset management of IoT?

### 3.2.1 Research Questions

To achieve the expected benefits of IoT adoption in asset management, a pragmatic approach to the interaction of human and technology is required. The adoption of IoT technology in asset management is a product of human actions and these actions determine the actual benefits to be gained. This is the reason why duality of technology theory is important to this research. A systematic study to create an overview of expected and perceived benefits and risks of IoT adoption in asset management through review of literature is presented in the research. The results confirm the duality that the ongoing adoption of IoT in asset management produces unexpected social changes that lead to structural transformation within the asset management organization. As seen below in Figure 3-1, the literature review helps us, in part, to answer Research Question 1, which asks how IoT can improve asset management?

Achieving expected benefits and avoiding unknown risks of asset management through IoT requires an awareness of the elements and behaviors of AMDIs and the ability to coordinate the changes and processes required. Therefore, a second objective of this literature review is to learn and understand what AMDIs are and how they behave. AMDIs represent information about physical reality. As reality changes, AMDIs might also be subject to change, but although physical infrastructures are often approached as CAS, the underlying AMDIs hardly are. Studying AMDIs as CASs has significant implications for our understanding of them and a CAS lens will help us to identify and better understand their key

elements and behaviors. As such, the literature review helps us, in part, to answer Research Question 2 which asks *what are the elements and behaviors of AMDIs that enable asset management through IoT*?

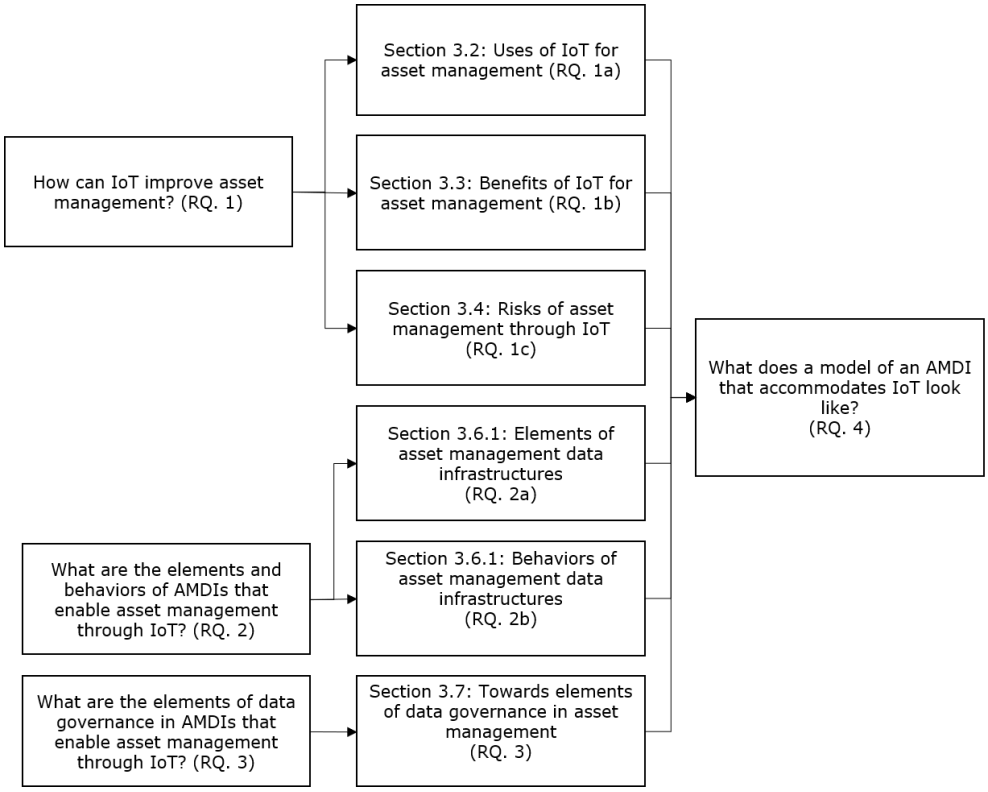


Figure 3-1: The relationship of the literature review to the research questions

This question helps us determine what the elements and behaviors of an AMDI are. Accepting AMDIs as CASs also means we need to understand the consequences for their development. One such consequence is that AMDIs, as CAS, are coordinated by schema. We identify the schema of AMDI as being embodied by data governance. Many asset management data management issues are often caused by a lack of data governance - the exercise of authority, control, and shared decision making over the management of AMDIs. Data governance provides organizations with the ability to ensure that data is managed appropriately, and that AMDIs can provide the right people with the right information at the right time. Despite its importance for coordinating data management, data governance has received scant attention by the

scientific community. Research has focused on data governance structures and there has been only limited attention given to the characteristics of data governance in an asset management setting. Using a CAS lens, this research derives a framework of data governance characteristics for the adoption of IoT in asset management. Characteristics provide insight into the goals of data governance, and viewing data governance through a CAS lens provides insight into how these goals may be achieved. As such, the literature review also helps us, in part, to answer Research Question 3 which asks *what are the elements of data governance in AMDIs that enable asset management through IoT*? This question helps us determine what the schema (data governance) of an AMDI, as CAS, entails.

### 3.2.2 Search Process

The search process entailed a digital search of the databases Scopus, Web of Science, IEEE explore, and JSTOR, using keywords relevant to the research question under discussion. The databases were selected because they include peer reviewed articles from a wide range of journals and conferences which accept academic papers related to information and data infrastructures in the asset management domain. The limited number of databases used may be a concern, as relevant papers may have been inadvertently omitted. We then performed a manual forwards and backwards search to identify relevant research that had not appeared in the initial searches until saturation was achieved. The final selection of papers was made using the following inclusion and exclusion criteria:

*Inclusion*
Peer-reviewed articles on the following topics, published between Jan 1st 2000 and June 30th 2016, were included:

- Use of IoT in AM:
  The keywords "*infrastructure*", "*IoT*" or "*Internet of Things*", "*data*", and "*use*" returned 324 hits.
- Benefits of IoT for AM:
  The keywords "*infrastructure*", "*IoT*" or "*Internet of Things*", and "*benefits*" returned 98 hits
- Barriers preventing the implementation of IoT in AM:
  The keywords "*infrastructure*", "Internet of Things" (or "IoT"), "impediments" or "barriers" or "risks" returned 67 hits.
- Elements and behaviors of AMDIs as CAS
  The keywords "*infrastructure*", "*IoT*" or "*Internet of Things*", and "*elements*" or "characteristics" returned 76 hits.

- Elements of Data Governance
  The keywords “data governance” and “principles” returned 17 hits.

*Exclusion*
After the manual forward and backward search, articles were excluded based on whether or not they included a theoretical discussion on the use or implementation of IoT generated data in asset management decision-making.

### 3.2.3 Data Collection

The data extracted from each study were:

- The source (journal or conference) and full reference.
- Main topic area.
- Summary of the study including the main research questions and the answers.
- Research question/issue.

### 3.2.4 Outline of the Literature Review

The reader should note that parts of this chapter have been published in: Brous, Janssen, Herder (2018), "Internet of Things adoption for reconfiguring decision-making processes in asset management", Business Process Management Journal, https://doi.org/10.1108/BPMJ-11-2017-0328. Section 3.2 discusses the potential uses of IoT in AMDIs. Parts of this section were published in the proceedings of the 2nd International Conference on Internet of Things, Big Data and Security (Brous et al., 2017). Sections 3.3 and 3.4 discuss the potential benefits and risks of IoT adoption in AMDIs respectively. Parts of these sections were published in the proceedings of the IFIP Conference on e-Business, e-Services and e-Society, in the proceedings of the 14th IFIP Electronic Government (EGOV) and 7th Electronic Participation (ePart) Conference (Brous et al., 2015b), and in the proceedings of the 15th International Conference on Electronic Business. Section 3.5 summarizes these benefits and risks. Section 3.6 discusses AMDIs as CAS. Parts of this section were published in the proceedings of Complex Adaptive Systems 2014 (Brous et al., 2014), Complex Adaptive Systems 2015 (Brous et al. 2015c), and Complex Adaptive Systems 2016 (Brous et al., 2016a). Section 3.7 discusses the role of data governance in AMDIs. Parts of this section were published in the proceedings of the 15th IFIP Electronic Government (EGOV) and 8th Electronic Participation (ePart) Conference (Brous et al., 2016b). Section 3.8 summarizes the literature review.

## 3.3 Uses of IoT in Asset Management

In this section we review and discuss literature with regards to how IoT is used in asset management as asked by research question 1a, "*How can IoT be used in asset management?*".

Infrastructure systems consist of many different types of assets that could have long life cycles. Infrastructure assets need to be maintained to ensure their optimal value over their entire (long) life cycles (Hassanain, Froese, & Vanier, 2003). Asset management helps asset management organizations realize value from infrastructure assets whilst balancing financial, environmental and social costs, risks, quality of service and performance related to assets (ISO 55000, 2014). As early as 2001 there were already many software tools for asset management (Hassanain et al., 2003; Vanier, 2001), and since then many data formats, data sources and pools of unstructured data have become available over the years. At a high level, asset management tooling should at minimum provide the following functionality (Hassanain et al., 2003; Vanier, 2001):

- Identification of assets
- Identification of performance requirements
- Assessment of asset performance
- Plan maintenance
- Manage maintenance operations
- Life-cycle costing analysis
- Life-cycle analysis and long-term service-life prediction
- Central repository for asset information

The explosive growth in data is due to a number of different enabling and driving technologies such as the widespread roll-out of fixed and mobile internet; the development of ubiquitous computing and the ability to access networks and computation in many environments (Kitchin, 2014). It is expected that IoT will be used in a variety of ways related both to the real-time measurement of the quality of assets and analyses of data as to trend analysis of historical data over time to reduce maintenance costs (Brous & Janssen, 2015b). The variety of using IoT enables further understanding of the conditions and factors for effective and sustainable adoption of new data sources. Following from that, we focus on the review of theoretical discussions in the relevant articles on the varied ways in which IoT is used.

In asset management and information technology (IT) research, an accepted and suitable way to review literature is through the distinction of three levels: strategic/political, tactical and operational (Ackoff, 1971; Ivanov, 2010). In this research we differentiate these levels based on the

time frame the decisions associated with each level: strategic 3-5 years, tactical 1<3, and operational <1 years. This distinction is also recognized in asset management literature via the roles of asset owner, asset manager and service provider (Woodhouse, 1997; Volker *et al.* 2012; CROW, 2017). In correspondence to this distinction, Table 3-1 summarizes the expected strategic, tactical and operational uses of IoT found in literature. The review reveals three expectations of IoT data. First, the literature expects that it will change performance measurement of infrastructure services, like applying statistical learning (Archetti, Giordani and Candelieri, 2015). Second, IoT data is expected to change the perception of infrastructure services, like perceiving sudden changes in temperature by which a fire could be detected (Hentschel, Jacob, Singer, & Chalmers, 2016) and the deterioration of the quality of assets over time (Brous, Janssen, Schraven, Spiegeler, & Duzgun, 2017). Finally, IoT data is expected to change improvement processes, for example through self-organizing resource planning. In the next sections, we discuss these uses of IoT.

### 3.3.1 Expected Strategic Uses of IoT Data in Asset Management

Decision support services include support for management at the tactical and strategic levels. IoT services are knowledge intensive and require collection of appropriate data contents, data analysis and reporting (Backman & Helaakoski, 2016). As such, statistical learning and network science is expected to play a critical role in converting data resources into actionable knowledge (Archetti et al., 2015). Due to increasing pressure on budgets and personnel as well as increased utilization of public utility infrastructure, public AM organizations increasingly need to intelligently manage their infrastructure with fewer resources (Rathore, Ahmad, Paul, & Thikshaja, 2016). By managing and analyzing various IoT data, it should be possible to create new services to achieve an efficient and sustainable infrastructure (Backman & Helaakoski, 2016; Hashi et al., 2015). IoT may bring an improved understanding of complex processes which is expected to help improve the efficiency of transport management and infrastructure services, and help with effective reporting (Kothari et al., 2015). Rathore et al. (2016) believe that smart management of traffic systems with the provision of real-time information to the citizen based on the current traffic situation should enhance the management performance of public AM organizations. Furthermore, improved granularity of trend analysis resulting from IoT data may help public AM

Table 3-1: Overview of expected uses of IoT data found in literature

| **Level** | **IoT data expected to change performance measurement of infrastructure service** | **IoT data expected to change perception of infrastructure service** | **IoT data expected to change improvement processes of infrastructure service** |
|---|---|---|---|
| Strategic use of IoT data | Decision support services (trend analysis) (Aono et al., 2016)<br>Reporting (Backman & Helaakoski, 2016; Kothari, Boddula, Ramaswamy, & Abolhassani, 2015) | Communication of long term planning and strategic choices (Backman & Helaakoski, 2016)<br>Improve perceived optimization of services (Sadeghi, Wachsmann, & Waidner, 2015) | Encourage proactive processes (Aono et al., 2016)<br>Encourage self-organization (Sadeghi et al., 2015)<br>Determine strategic changes to infrastructure (Backman & Helaakoski, 2016) |
| Tactical use of IoT data | Cost management (Aono et al., 2016; Archetti, Giordani, & Candelieri, 2015)<br>Time management (Aono et al., 2016)<br>Planning (Archetti et al., 2015)<br>Post-events evaluations (Hashi et al., 2015; Tao, Ling, Guofeng, Hongyong, & Quanyi, 2014) | Communication of short term planning and actions (Archetti et al., 2015)<br>Improve perceived quality of services (Archetti et al., 2015)<br>Public enactment (Tien et al., 2016) | Enable directed procedures (Aono et al., 2016)<br>Enable efficient recovery (Tien et al., 2016)<br>Control event occurrence (Parkinson & Bamford, 2016; Tao et al., 2014)<br>Improve utilization of existing infrastructure (Hentschel et al., 2016; Koo, Piratla, & Matthews, 2015) |
| Operational use of IoT data | Improve efficiency of monitoring (Ahlborn et al., 2010)<br>Improve quality of monitoring (Hentschel et al., 2016; Phares, Washer, Rolander, Graybeal, & Moore, 2004)<br>Improve operational decision-making (Neisse et al., 2016)<br>Improve productivity (Hentschel et al., 2016) | Communication of operational activities (Hentschel et al., 2016)<br>Improve perceived quality of delivery (Ahlborn et al., 2010) | Improve efficiency of operations (Zhang et al., 2015)<br>Improve effectiveness of operations (Neisse et al., 2016) |

organizations in being proactive with maintenance, reducing the chances of catastrophic failure (Aono et al., 2016). IoT may also be used to improve service optimization through self-organization (Sadeghi et al., 2015). Self-organizing systems that optimize themselves with regard to resource availability and consumption may enable optimization according to usage and de-centralized long-term support (Sadeghi et al., 2015).

### 3.3.2 Expected Tactical Uses of IoT Data in Asset Management

IoT infrastructure could potentially be used to reduce costs in terms of time and money (Aono et al., 2016), as traditional methods of inspecting infrastructure, such as highway structures and bridges, for damage are often reactive in nature and require significant amounts of time and use of costly equipment. Aono et al. (2016) suggest that an infrastructure-monitoring network could be used to quickly assess damage to infrastructure so that maintenance procedures could be directed to areas that need immediate attention. In this way, IoT may play a significant role in the channeling and transmission of data through efficient use of technology (Sakhardande, Hanagal, & Kulkarni, 2016).

IoT is expected to be able to provide users with information on costs, time, environmental impact and perceived quality of services (Archetti et al., 2015). When IoT data becomes available regarding a particular hazard, there may be opportunities to control hazard occurrence and recover using these data sources (Parkinson & Bamford, 2016; Tao et al., 2014) and trigger analysis with events that affect measurement, such as repair or maintenance (Hentschel et al., 2016; Koo et al., 2015). By specifying events (Hashi et al., 2015; Tao et al., 2014), it should be possible to obtain a set of data before and after an event to be used for analysis and evaluations, taking the effect of the event into consideration. It is also expected that IoT will improve the utilization of existing infrastructure (Hentschel et al., 2016; Koo et al., 2015). For example, Koo et al. (2015) suggest that an automated system condition monitoring based on IoT including leak detection can optimizing water supply, production, and water consumption.

IoT may enable more effective and efficient AM planning according to variations in user preferences (Archetti et al., 2015) by providing decision support functionalities which identify and address criticalities in public utility infrastructure. Archetti et al. (2015) give the example that commuters may use socially aware and collective intelligence based on functionalities of IoT to make individually informed mobility decisions.

However, for this to be realized, the collected data must have significance for operations and services such as inventory, usage, environmental management, and events. Also, quality of the information must be considered with regards to multiple aspects and dimensions. IoT data should be "fit-for-use" (Backman & Helaakoski, 2016; Cao et al., 2016). For example, closures of bridges that are part of major transportation arteries tend to be major events. These events often result in "tweets" that point to the same incident (Tien et al., 2016), which if analyzed correctly may improve service efficiency and enable more effective recovery.

### 3.3.3 Expected Operational Uses of IoT Data in Asset Management

In order to keep infrastructure such as bridges safe and functioning, regular inspections to determine the condition of the asset are a necessity (Ahlborn et al., 2010; Neisse et al., 2016). For example, traditional inspections of bridges are usually visual assessments by trained personnel where all the asset's component conditions are observed once every three to six years, and are summarized into one report (Phares et al., 2004). After the inspection is done, asset managers must decide what maintenance interventions are needed based on these inspection reports. However, as is shown by Kallen & van Noortwijk (2005), inspection reports of bridges can be biased by subjective judgements of the experts or by lack of information. This can eventually result in inaccurate statements which may lead to the failure to perform maintenance or unnecessary maintenance activities (Phares et al., 2004).

IoT data may make it possible to remotely observe the condition of objects and thereby enhance the available information on the condition of public infrastructure (Ahlborn et al., 2010). IoT data is expected to allow users to monitor current environmental conditions affecting the asset. Event processing should be able to support individual, complex events if these events are defined by individual users for localized events (Hentschel et al., 2016). Examples given by Hentschel et al. (2016) are sudden increases in sound, light and temperature, which could indicate a fire or an explosion. Hentschel et al. (2016) expect that when an event is triggered alarms could be issued.

Environmental factors such as temperature and air quality can have significant effects on productivity (Hentschel et al., 2016). Smart assets may be able to monitor status parameters, analyze this data and reach some conclusions, considering at the same time tensions such as

cost and efficiency with regards to environment preservation (Moreno et al., 2014). As such, IoT data is also expected to play a role in increasing public safety and security (Neisse et al., 2016) through, for example, active road safety, emergency vehicle warning or collision risk warning.

IoT data is expected to be leveraged for increased efficiency in various public service applications such as inspection schedules, public facility management, urban infrastructure maintenance, intelligent transportation services, and emergency situation monitoring (Zhang et al., 2015). By enabling individuals and organizations to share real time data, IoT may enable appropriate data services to the consumers (Kothari et al., 2015). The expectation is that IoT will be used for key decision making in operational activities. It is expected that IoT will be used in a variety of ways related both to the real-time measurement and analysis of data as to trend analysis of historical data over time (Brous & Janssen, 2015b). Following Ivanov (2010), we list the benefits and risks of IoT adoption in asset management according to strategic/political, tactical and operational divisions. In the following section, the expected benefits of IoT adoption are explored, followed by a discussion of the expected risks of IoT adoption.

## 3.4 Expected Benefits of Asset Management Through IoT

The main enabling factor for IoT adoption in AM is the combination and integration of several technologies such as identification and tracking technologies, sensor networks, communication protocols, (Atzori et al., 2010), Radio Frequency Identification technology, Electronic Product Code technology, and ZigBee technology (Chen & Jin, 2012). Cameras and microphones can be used to collect evidence when there is a robbery or a riot and devices can measure the concentration of fine particles. As such, sensors can be used for enabling public safety and compliance to regulations for example. In this way it may provide a more effective control mechanism (Atzori et al., 2010; Chui, Löffler, & Roberts, 2010; Chen & Jin, 2012; Gubbi et al., 2013; Boulos & Al-Shorbaji, 2014).

According to Boos et al. (2013), IoT applications generally allow automation of data capture, making manual data capture unnecessary. IoT results in a large amount of big data. Literature shows that this might have two important benefits for AM. Firstly, making data and information available to the public greatly improves organizational transparency (Castro, 2008a). Increased openness and transparency helps ensure proper oversight and reduces waste. Secondly, enabling consumer self-

service in this way can empower citizens and business to take decisions through better access to information by making use of the vast amount of data collected by IoT and the collective wisdom of the crowds (Hounsell et al., 2009; Fleisch, 2010; Atzori et al., 2010; Chen & Jin, 2012; Gubbi et al., 2013; Boulos & Al-Shorbaji, 2014).

Fleisch (2010) identifies seven value drivers for the IoT which result in potential business benefits: 1. The simplified manual proximity trigger increases job satisfaction, empowers the public by enabling consumer self-service, reduces labor costs and improves data quality (Bi, Da Xu, & Wang, 2014); 2. The automatic proximity trigger reduces fraud related costs, process failure costs, and labor costs; 3. the automatic sensors trigger helps improve service quality by providing individual and prompt process control, increasing process efficiency and effectiveness; 4. Automatic product security reduces cost of process failure due to fraud, reduces the cost of process security and helps increase consumer trust; 5. Simple, direct user feedback improves service efficiency and effectiveness by helping processes become more accurate, more flexible, and faster; 6. extensive user feedback improves trust by enabling new forms of public contact, providing new communication opportunities and supporting additional service revenues; 7. mind changing feedback allows for the identification of trends, and enables new services (Fleisch, 2010).

Chui et al. (2010) define two broad categories for IoT applications, "Information and Analysis" and "Automation and Control". In Information and Analysis, decision-making services are improved by receiving better and more up to date information from networked physical objects which allows for a more accurate analysis of the current status-quo with regards to tracking, situational awareness, and sensor-driven decision analytics. IoT technologies can cost effectively collect data about work processes without time consuming physical counts (Boos et al., 2013). In Automation and Control, outputs received from processed data and analysis are acted upon to improve efficiency, effectiveness and to enforce compliancy.

Haller et al. (2009) draw on the work of Fleisch, Sarma, & Subirana (2006) and identify two major paradigms from which business value can be derived: real-world visibility, and business process decomposition. Sensors make it possible for a public organization to better know what is happening in the real world. In business process decomposition, the decomposition and decentralization of existing processes increases service flexibility and service effectiveness, allows better decision making and can lead to new revenue streams (Bi et al., 2014; Haller et al., 2009). Eventually, the capability of IoT to inform and automate can subsequently

lead to a transformation of existing business processes (Boos et al., 2013).

The benefits of IoT technologies for AM are primarily derived from the availability of more granular information which is automatically collected and readily shareable soon after it is generated (Harrison, 2011; Vesyropoulos & Georgiadis, 2013). This provides better analysis of track and trace information, and helps balance supply and demand (Harrison, 2011). According to Lytras, Mathkour, Abdalla, Yáñez-Márquez, & De Pablos (2014), the capacity of any object to be considered as a peer of fully operational data, and as a potential receiver and transmitter of critical information is critical for the realization of more advanced business scenarios. Figure 3-2 below summarizes the potential benefits of IoT for asset management.


Figure 3-2: Possible benefits of IoT for asset management

In short, IoT can deliver a variety of benefits related both to the real-time measurement and analyses of sensor data efficiency of services, improved effectiveness of services, and improved flexibility of services as to trend analysis of historical data over time.

## 3.5 Expected Risks of Asset Management Through IoT

Organizations are increasingly turning to IoT as new sources of data, derived from continuously monitoring a wide range of things within a variety of situations, becomes available. However, there are several technological and regulatory challenges that need to be addressed. Scarfo (2014) believe that the most important of them are related to data

ownership, security, privacy and sharing of information. Disclosure of user data could reveal sensitive information such as personal habits or personal financial information. Unauthorized access to this information can severely impact user privacy (Hummen, Henze, Catrein, & Wehrle, 2012; Fan, Wang, Zhang, & Lin, 2014; Skarmeta, Hernandez-Ramos, & Moreno, 2014). Data produced by IoT devices can be combined, processed and analyzed, creating additional insights, so it is important to allow access to data generated by other IoT devices, whilst preventing the unauthorized access and misuse of this information (Skarmeta et al., 2014). However, as the IoT becomes more widespread, new security issues become evident (Ortiz, Lazaro, Uriarte, & Carnerero, 2013). Whilst these technologies have been widely investigated for traditional technologies such as relational databases, so far there are no convincing solutions for providing fine-grained access control. This hinders the uptake of IoT in applications dealing with sensitive data (Hummen et al., 2012; Fan et al., 2014; Harris, Wang, & Wang, 2015).

A lack of policies and regulations regarding IoT can also greatly impede the implementation and application of IoT in AM. Organizations need to develop policy and regulations and position themselves carefully within this arena (Stephan et al., 2013; Yazici, 2014; Harris et al., 2015). In this regard, organizations should consider the role they play in enabling IoT development. Market forces of supply and demand can play substantial roles in the success or failure of IoT (Wiechert, Thiesse, Michahelles, Schmitt, & Fleisch, 2007; Misuraca, 2009; Qiao & Wang, 2012; Fan et al., 2014). The internal mechanism of explosive growth is that the whole networking industry chain achieves linkage development between supply and demand (Qiao & Wang, 2012), but there is a danger that AM may miss this linkage development due the chain of IoT industry being blocked by a tactical risks such as a lack of technology breakthroughs, standards bottlenecks and cost risks (Qiao & Wang, 2012).

According to Zeng, Guo, & Cheng (2011) home appliances, for example, are usually directly integrated whilst RFIDs are indirectly integrated through a RFID reader with an embedded server. It is not uncommon for a system to utilize both methods. However, IoT adoption for asset management purposes often requires that many devices be integrated with the existing Internet. These devices can be technologically highly diverse, presenting interoperability challenges. The heterogeneity at the device level is, in this way, a serious impediment to IoT adoption in AM (Zeng et al., 2011). This is especially complex as consumers of data are also heterogeneous. Furthermore, different applications might

implement disparate data processing or filtering. Zeng et al. (2011) believe that it is these heterogeneity traits of the overall system that make the design of a unifying framework and the communication protocols a very challenging task, especially with devices with different levels of capabilities. This is underlined by Qian & Che (2012) as they determine that searching in IoT requires a methodology of architecture design of search engines as designing an appropriate search engine for IoT is non-trivial.

According to a number of researchers, the success of user-centric services based on IoT technology depends greatly on the willingness of people to share their information (Fan et al., 2014; Kranenburg et al., 2014; Nam & Pardo, 2014; Zeng et al., 2011). Kranenburg et al. (2014) believe that this willingness is predominantly dependent on the perception of people: the perceived trust and confidence in IoT and the perceived value that the IoT generates for them. The greater the trust of users in the IoT, the greater their confidence in the system and the more willing they will be to participate. A lack of trust in the system can be a strong impediment to the effectiveness of IoT in AM.

Operational risks include human capital issues such as difficulty in employing qualified personnel, lack of specialists, and personnel skill shortage to operate new applications (Speed & Shingleton, 2012; Yazici, 2014), as well as insufficient IoT oriented training and educational activities (Harris et al., 2015). There is also a reluctance to change or to learn new technology as a barrier (Pedro M. Reyes & Patrick Jaska, 2007; Speed & Shingleton, 2012; Reyes, Li, & Visich, 2012; Yazici, 2014). Reyes et al. (2012) includes calculating the return on investment and the payback period in this category. Many researchers also cite high development and implementation costs as an important impediment to the implementation and application of IoT in AM (Qiao & Wang, 2012; Fan et al., 2014; Nam & Pardo, 2014; Yazici, 2014; Harris et al., 2015). A fully functional IoT system based on RFID technology can be substantial. By way of example, Yazici (2014) quotes Wal-Mart's vendors as having spent US$1 to US$3 million on a RFID implementation.

Operational risks also include technical issues such as limitations in information technology (IT) infrastructural capabilities (Wiechert et al., 2007; Prasad et al., 2011; Zeng et al., 2011; Hummen et al., 2012; Fan et al., 2014; Kranenburg et al., 2014; Scarfo, 2014; Yazici, 2014), and data management (Blackstock & Lea, 2012; Gilman & Nordtvedt, 2014; Stephan et al., 2013). According to Scarfo (2014), the main technological challenges include architecture, energy efficiency, security, protocols and quality of service. An important enabler for the IoT is to permit others to

access and use the things that have been published publicly on the internet. It should be possible for users to make use of things that others have shared and to make use of things in their own applications, perhaps in ways unanticipated by the owner of the thing (Blackstock & Lea, 2012). This requirement means we need a sophisticated set of mechanisms to publish and share things and ways to find and access those things (Blackstock & Lea, 2012). Qian & Che (2012) also describe search locality, scalability and real-time processing as strong barriers to IoT implementation. According to Qian & Che (2012), existing searching techniques are based on remote information sharing and often fail to effectively support local search of physical objects. Figure 3-3 below summarizes the potential risks of asset management through IoT.

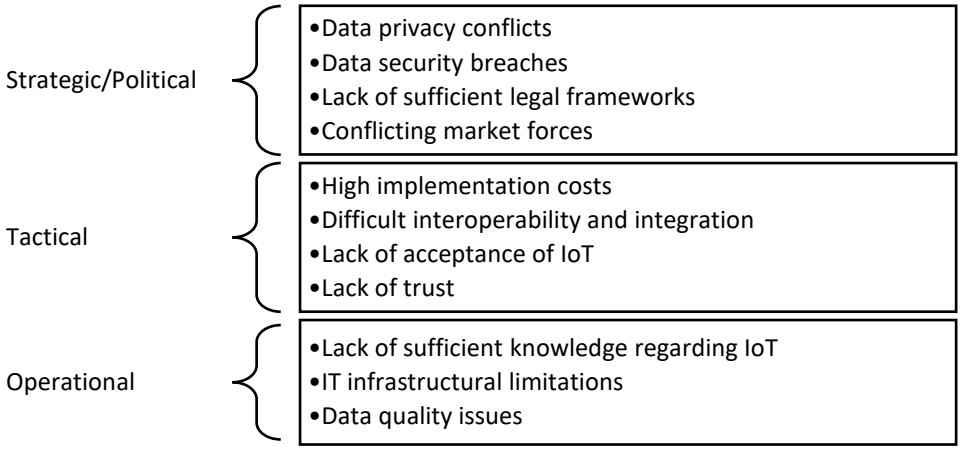


Figure 3-3: Possible risks of IoT adoption in asset management organizations

In short, asset management through IoT faces a variety of risks related to the proper use, such as privacy and security, for example, as well as proper management of the data collected by the vast number of interconnected things.

## 3.6 Summary of Expected Benefits and Risks of Asset Management Through IoT

Initial research on IoT adoption tended to focused on the potential benefits of IoT adoption, but more recent debates have increasingly stressed that IoT adoption may also introduce potential risks to the organization (Castelnovo, Misuraca, & Savoldelli, 2015; van Waart,

Mulder, & de Bont, 2015). Van Waart et al. (2015) go so far as to suggest that deploying IoT technologies to increase efficiency of public services such as public transportation, traffic management, or energy management does not necessarily lead to an increased well-being of citizens. By way of example, van Waart et al. (2015) cite Hollands' (2008) differentiation between cities that focus om IoT purely for economic prosperity and those that seek to become sustainable and inclusive. From an asset management perspective, Hollands (2008) argues that cities should pay close attention to societal needs, and not necessarily rely on IoT to automatically manage public assets without direction, as this requires new organizational structures in the use of information technology by businesses, government, communities, and the public. Table 3-2 below summarizes the potential benefits and risks of IoT adoption in relation to examples found in the literature as answer to Research Question 1.

Table 3-2: Expected organizational benefits and potential risks of asset management through IoT

| **Context** | **Expected Benefits** | **Literature Examples** | **Potential Risks** | **Literature Examples** |
|---|---|---|---|---|
| Strategic | Improved forecasting and trend analysis | (Chui et al., 2010; Harrison, 2011) | Data privacy conflicts | (Fan et al., 2014) |
| | Promoting transparency | (Gubbi et al., 2013; Hounsell et al., 2009) | Data security breaches, Lack of sufficient legal frameworks | (Harris et al., 2015; Kranenburg et al., 2014; Scarfo, 2014; Stephan et al., 2013) |
| | Citizen empowerment | (Boulos & Al-Shorbaji, 2014; Coetzee & Eksteen, 2011) | Conflicting market forces | (Misuraca, 2009; Qiao & Wang, 2012) |
| Tactical | Improved planning with regards to management and maintenance | (Hounsell et al., 2009) | Lack of acceptance of IoT | (Gilman & Nordtvedt, 2014; Speed & Shingleton, 2012) |
| | More efficient regulations | (Hounsell et al., 2009) | Difficult interoperability and integration | (Blackstock & Lea, 2012; Wiechert et al., 2007) |

| Context | Expected Benefits | Literature Examples | Potential Risks | Literature Examples |
|---|---|---|---|---|
| | More efficient enforcement of regulations | (Chui et al., 2010; Gubbi et al., 2013) | Lack of trust | (Kranenburg et al., 2014; Zeng et al., 2011) |
| | Reduction of costs,<br><br>New revenue streams | (Bi et al., 2014; Haller et al., 2009)<br><br>(Fleisch, 2010; Vesyropoulos & Georgiadis, 2013) | High implementation costs | (Nam & Pardo, 2014; Qiao & Wang, 2012) |
| Operational | Improved efficiency of services | (Boulos & Al-Shorbaji, 2014; Hounsell et al., 2009) | Lack of sufficient knowledge regarding IoT | (Speed & Shingleton, 2012; Yazici, 2014) |
| | Improved effectiveness of services | (Boulos & Al-Shorbaji, 2014; Hounsell et al., 2009) | Data quality issues | (Hummen et al., 2012; Prasad et al., 2011; Stephan et al., 2013) |
| | Improved flexibility of services | (Boulos & Al-Shorbaji, 2014; Hounsell et al., 2009) | IT infrastructural limitations | (Hummen et al., 2012; Wiechert et al., 2007) |

The literature tends to emphasize the assumed benefits of IoT without providing empirical evidence. Furthermore, the risks were often risks that might occur during implementation, and little attention has been given to long term consequences of IoT adoption in organizations. These aspects need to be investigated and are dealt with in the exploratory case studies in Chapter 4. The expected benefits and potential risks of asset management through IoT provide insight into how IoT may change asset management. However, achieving these benefits and mitigating potential risk requires an understanding of the characteristics of AMDIs and how AMDIs may react to new technologies such as IoT. The following section, section 3.6 investigates the elements and behaviors of AMDIs, and discusses how AMDIs, as CAS, may be modelled.

## 3.7 Elements and Behaviors of AMDIs

AMDIs have been identified as CAS and their complex nature is the reason for the difficulties encountered in trying to understand and assess them (Grus et al., 2010). As such, modelling AMDIs is a complex undertaking. For example, it is difficult to attribute success or failure to one or more

concrete factors. In other words, because AMDIs are complex it is difficult to track cause-and-effect relationships. Traditional approaches to modelling behaviors of large systems through reductionism have often failed to analyze complex levels and fully describe behavior (Haghnevis & Askin, 2012). Reductionism is the study of behaviors of large systems by decomposing the system into components, and analyzing system behavior by aggregating component behaviors (Haghnevis & Askin, 2012). Moreover, the dynamic and uncertain relations between the AMDI elements are hard to predict and control.

All AMDIs have a unique character and behave differently. This makes it difficult to implement data infrastructures in different environments in the same way and with the same outcomes (Grus et al., 2010). As such, Jennings (2001) argue that analyzing, designing, and implementing complex software systems as a collection of interacting, autonomous agents affords a number of significant advantages over traditional methods. For example, Jennings (2001) shows that agent-oriented decompositions are an effective way of partitioning the problem space of a complex system, whilst the key abstractions of the agent-oriented mindset are a natural means of modeling complex systems. Furthermore, Jennings (2001) argue that the agent-oriented philosophy for modeling and managing organizational relationships is appropriate for dealing with the dependencies and interactions that exist in complex systems.

Viewing data infrastructures as CAS means that decision-makers may understand better the dependencies involved (Janssen & Kuk, 2006), acknowledging that exerting a hierarchical and tight control over complex systems spanning multiple levels is impossible. Instead, one must take into account the various typical characteristics of CAS (Herder et al., 2008).

CASs are often described as systems of interactive, mutually interdependent, individual elements which merge over time into coherent forms, adapting and organizing themselves without any singular entity deliberately managing or controlling them (Holland, 1992). CASs are dynamic systems which are able to adapt within and evolve with a changing environment (Chan, 2001). Schools of fish provide us with a good example of a CAS. Even when shoaling, individual fish continually adapt to changes in their environment by adapting the distance between themselves and predators. Individual fish follow simple rules and interact with others to form a cohesive and dynamic whole designed to combat the threat that the predator poses. In such cases, CASs can be used to explain how the system-level response is affected by individual action. As

such, Chan (2001) believes that change should be seen as a co-evolution of all the related elements within the system, rather than as being an adaptation to a separate environment.

Despite the plethora of examples used by researchers to describe what a CAS is, there appears to be little agreement as to an exact definition and what the characteristics of a CAS should be. For example, Wallis (2008) deconstructs twenty versions of CAS theory related to the management science discipline and concludes that the variety of definitions is result of the situation of the definitions in different research fields. In this research our focus is on data infrastructures. We follow Grus et al. (2010), whose research field is spatial data infrastructures, and we use the definition given by Barnes et al. (2003, p. 276): CASs can be defined as, "*open systems in which different elements interact dynamically to exchange information, self-organize and create many different feedback loops, relationships between causes and effects are nonlinear, and the systems as a whole have emergent properties that cannot be understood by reference to the component parts*".

CAS elements are sets of system physicalities that together make CASs different from other systems. Similarly, CAS behaviors are the distinctive collection of functions and operations that make CAS behavior unique. Functional behavior being the behavior required to achieve a purpose and operational behavior being how the CAS achieves a purpose. Few researchers have made this distinction when defining CAS characteristics in the information systems domain, and there have been a number of calls for attention to this topic (Grus et al., 2010; Janssen & Kuk, 2006). The contribution of this research is to clarify the characteristics of CASs with regards to data infrastructures by cataloguing them according to their elements or behaviors. Table 3-3 and Table 3-4 below show the findings of the review.

Table 3-3: Elements of CAS theory by authors relevant to AMDIs

| **Elements** | **Literature** |
|---|---|
| Components | (Grus et al., 2010; Haghnevis & Askin, 2012; Rupert, Rattrout, & Hassas, 2008; Sutherland & van den Heuvel, 2002) |
| Agents | (Bollinger & Dijkema, 2012; Brown, Furneaux, & Gudmundsson, 2011; Cherinka, Miller, & Smith, 2005; Choi, Nazareth, & Jain, 2010; Furneaux, Brown, & Gudmundsson, 2008; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Kim & Kaplan, 2006; Rupert, Rattrout, & Hassas, 2008; Sherif & Xing, 2006) |

| Elements | Literature |
|---|---|
| Schema | (Choi, Nazareth, & Jain, 2010; Furneaux, Brown, & Gudmundsson, 2008; Grus et al., 2010; Janssen & Kuk, 2006; Janssen, Chun, & Gil-Garcia, 2009; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Rupert, Rattrout, & Hassas, 2008; Sherif & Xing, 2006; Sutherland & van den Heuvel, 2002) |
| Dynamic, rugged environments | (Choi, Nazareth, & Jain, 2010; de Man, 2006; Kim & Kaplan, 2006; Merali, 2006; Sherif & Xing, 2006) |

Table 3-4: Behaviors of CAS theory by authors relevant to AMDIs

| Behaviors | Literature |
|---|---|
| Dynamism | (Cherinka, Miller, & Smith, 2005; Choi, Nazareth, & Jain, 2010; Eoyang & Berkas, 1999; Grus et al., 2010; Hanseth & Lyytinen, 2010; Janssen & Kuk, 2006; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Kim & Kaplan, 2006; Merali, 2006; Rupert, Rattrout, & Hassas, 2008; Sutherland & van den Heuvel, 2002) |
| Connectivity | (Choi, Nazareth, & Jain, 2010; Man, 2006; Eoyang & Berkas, 1999; Haghnevis & Askin, 2012; Janssen & Kuk, 2006; Janssen, Chun; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Kim & Kaplan, 2006; Merali, 2006; Rupert, Rattrout, & Hassas, 2008; Sherif & Xing, 2006; Sutherland & van den Heuvel, 2002) |
| Adaptation | (Bollinger & Dijkema, 2012; Brown, Furneaux, & Gudmundsson, 2011; Cherinka, Miller, & Smith, 2005; de Man, 2006; Furneaux, Brown, & Gudmundsson, 2008; Grus et al., 2010; Haghnevis & Askin, 2012; Janssen & Kuk, 2006; Janssen, Chun, & Gil-Garcia, 2008; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Kim & Kaplan, 2006; Merali, 2006; Rupert, Rattrout, & Hassas, 2008; Sherif & Xing, 2006; Sutherland & van den Heuvel, 2002) |
| Emergence | (Bollinger & Dijkema, 2012; Brown, Furneaux, & Gudmundsson, 2011; Cherinka, Miller, & Smith, 2005; Eoyang & Berkas, 1999; Furneaux, Brown, & Gudmundsson, 2008; Hanseth & Lyytinen, 2010; Janssen & Kuk, 2006; Janssen, Chun, & Gil-Garcia, 2008; Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008; Kim & Kaplan, 2006; Merali, 2006; Rupert, Rattrout, & Hassas, 2008) |

### 3.7.1 Elements of AMDIs

CASs consist of relatively stable and simple *components* (Grus et al., 2010; Haghnevis & Askin, 2012; Rupert et al., 2008; Sutherland & van den Heuvel, 2002), building blocks which are the constituent parts of the system. The overall behavior of a CAS emerges from the activities of lower-level components. This emergence is the result of an organizing

force that can overcome a variety of changes to these components although, typically, a complex system will die when an essential component is removed (Miller & Page, 2009). Brous, Overtoom, Herder, Versluis, & Janssen (2014) have identified three essential components of data infrastructures, namely *data, people* and *technology*. Technology can also be further separated into *hardware*, the collection of physical components that constitute an information system, and *software*, that part of an information system that consists of computable instructions. People and, increasingly, technology are impacting the data infrastructure through *agency*. An agent is something or somebody that "can be viewed as perceiving its environment through sensors, and acting upon that environment through actuators" (Gong, 2012, p. 75). When people or things act (or react) to an environment, that environment can be changed in unexpected ways (Brous & Janssen, 2015a).

Generally, actors perform activities according to a *schema*, or shared rules which are embodied by norms, values, beliefs, and assumptions (Choi, Dooley, & Rungtusanatham, 2001). But when internal or external actors act, the *environment* in which data infrastructures exist may change often and quickly, forcing the data infrastructure to evolve and adapt to these changes. Figure 3-4 below depicts the relationships between the elements of AMDIs. This section continues by further discussing each these *elements* of data infrastructures in brief.

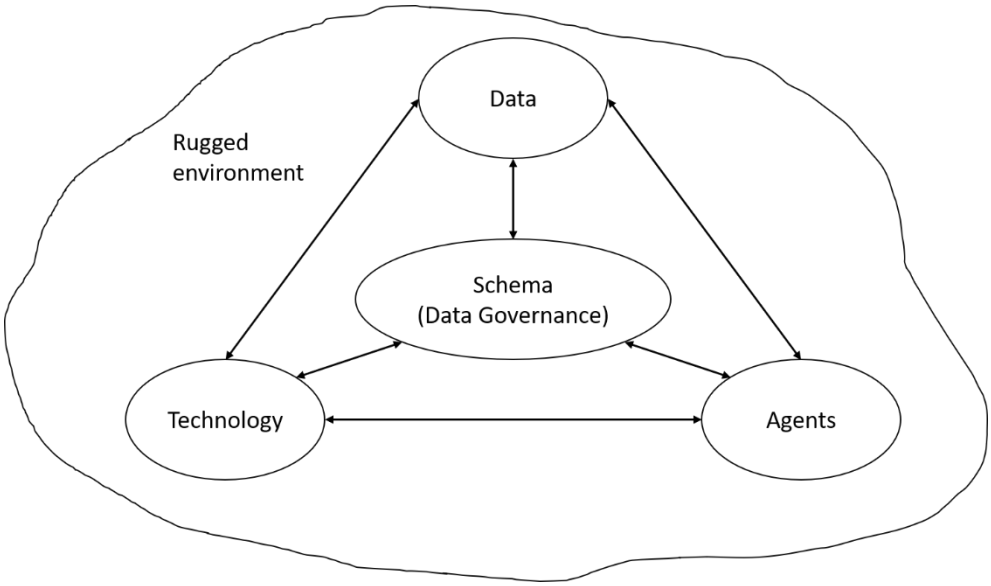


Figure 3-4: Relationships between elements of AMDI

*Data* has long been recognized as a core component of information systems and has been generally defined as the measure or description of objects or events (Checkland & Holwell, 1997; Kettinger & Li, 2010). The term "data" is often used in everyday terminology to refer to either raw data or to information (Khatri & Brown, 2010; Lin et al., 2007; Wende & Otto, 2007). In fact there is an important difference between the two (Kettinger & Li, 2010). As such, the scope of data infrastructures is difficult to define. The term, "data" is often distinguished from "information" by referring to data as raw data, and referring to information as data put in a context or data that has been processed (Huang et al., 1999; Price & Shanks, 2005).

The inherent challenge with these definitions occurs when data and information is registered and digitalized. From an IS perspective, data, and information can both take digital forms and, in these forms, are often, in practice, collectively referred to as data. For example, in an IoT environment, sensors such as temperature gauges make observations or measurements about an object or its environment, which may be registered in a system and is often referred to as raw data. This data can also often be enriched with other descriptors which help identify an object or thing, or, the environment, infrastructure, system or network in which the sensors, object or thing can be found. An example of this would be a name given to a person or object. In practice, these identifiers are often referred to as "master data" (Otto, 2012; Vilminko-Heikkinen, Brous, & Pekkola, 2016). Data can also enter a data infrastructure as the description of an event, such as commercial credit card purchases, stock market trades, or HTTP requests to a web server. This type of data is often known as "transactional data" (Bester, 2016).

But for information to be gained from all this data, context is required. This contextual data is gained from data which describes the data that is being created, often referred to as "metadata". Often, metadata also provides data about the sensor itself or about the object or thing that is being sensed. Metadata is often defined as data about data (Bargmeyer & Gillman, 2000; Khatri & Brown, 2010). As such, we must also recognize that metadata is also data. According to Khatri & Brown (2010), metadata describes what the data is about and provides a mechanism for a concise and consistent description of the representation of data, thereby helping interpret the meaning or "semantics" of data. As such, metadata can also be stored and managed in a database, often called a registry or repository (Bargmeyer & Gillman, 2000). Khatri & Brown (2010) describe different types of metadata as being physical, domain independent, domain-specific, and user metadata which play roles

in the discovery, retrieval, collation and analysis of data. According to Khatri & Brown (2010), physical metadata includes information about the physical storage of data; domain-independent metadata includes descriptions such as the creation or modification of data and the authorization, audit and lineage information related to the data; and user metadata includes annotations that users may associate with data items or collections.

Information can be gained by combining data (from the registration of observations, measurements, decisions or transactions) with metadata (data which provides context). In practice, this information is often stored in within data stores such as data warehouses (Holmes et al., 2014) and visualized in the form of reports. The build-up of this information over time becomes knowledge which is also often stored digitally within knowledge management systems (Lin, 2014). The lines of responsibility may often become blurred as multiple users combine multiple data sources and data types to create multiple information products.

*Technology* within data infrastructures is required to manage connected data resources. This technology must support the data management process (Thomas et al., 1994). The general problem of retrieval faced by data analysts is that a vast quantity of data is available, but the nature, quality, structure, type, and precise location are often not known (Nebert, 2004; Roberts et al., 2006; Thomas et al., 1994). Furthermore, development issues incurred by legacy and heterogeneous systems drive the need for interoperability. According to Yue, Sun, Li, Rehman, & Yang (2015, p. 1298) the primary value of IoT is "the sharing of information between things and things or between people and things". Yue et al. (2015, p.1299) summarize the basic characteristics of things as "comprehensive perception", "reliable transmission" and "intelligent processing". Comprehensive perception is described as including observations or measurements "by using perception, acquisition and measurement technology" (Yue et al., 2015, p.1299). Reliable transmission means ensuring that the objects have access to information networks and can realize reliable information interaction and sharing through communications networks. Intelligent processing is described as the analysis of sensor data by using a variety of intelligent computing technology, to "achieve intelligent decision-making and control" (Yue et al., 2015, p. 1299). As such, data infrastructures are increasingly being migrated to cloud solutions whereby service providers provide the hard and software necessary to manage the data resources (Vaquero, Rodero-Merino, Caceres, & Lindner, 2008). According to Vaquero et al. (2008),

infrastructure providers manage a large set of computing resources, such as storing and processing capacity and are able to split, assign and dynamically resize these resources to build ad-hoc systems as demanded by customers. This is commonly known as the Infrastructure as a Service (IaaS) scenario (Mell & Grance, 2011). Cloud systems can also provide the software platform where systems run on. This is known as Platform as a Service (PaaS) (Mell & Grance, 2011; Vaquero et al., 2008). Finally, there are services which run applications. An example of this is the online alternatives of typical office applications such as word processors. This scenario is often called Software as a Service (SaaS) (Mell & Grance, 2011; Vaquero et al., 2008).

In a CAS, multiple *agents* often interact with one another in large variety of ways. Agents are entities that have the ability to intervene meaningfully in the course of events (Choi et al., 2001). Data infrastructures include people as agents. People are seen as a key element in data infrastructures as people are responsible for the decision making, design, implementation, and use of the data infrastructure (Anderies, Janssen, & Ostrom, 2004; Grus et al., 2010; Rajabifard, Feeney, & Williamson, 2002). With regards to people, knowledge management is of utmost importance (Ure et al., 2009). Local knowledge is often central to the ongoing maintenance of data, particularly in the face of unanticipated and unpredictable changes in local context and practice (Ure et al., 2009) as people have a direct influence on the role of organizational culture within data infrastructures, and effective data infrastructures are developed and applied around commonly felt needs (de Man, 2006). Significantly, artificial intelligence is becoming more and more prevalent in service oriented environments, especially in the form of software commonly known as "bots' (Gianvecchio, Xie, Wu, & Wang, 2011). As such, artificial intelligence and robotics as agents are beginning to play an important role in the development of data infrastructures as more and more infrastructure management processes become automated. Agents have varying degrees of connectivity with other agents, through which information and resources can flow. They possess schema that determine the states and rules of their behavior (Choi et al., 2001).

*Schema* refers to shared rules which are embodied by norms, values, beliefs, and assumptions (Choi et al., 2001). That agents use rules to make decisions is reflected in the notion that agents have frames of reference or schemata by which they interpret and evaluate information (Furneaux et al., 2008). Roles and rules are agreements which help agents define meaning, as, according to Cherinka et al. (2005), CASs can have competing stakeholders and competing schemata. The agreements

that prove to be the most resilient are the ones that are ultimately accepted (Cherinka et al., 2005). The schema of AMDIs is embodied by data governance. According to Khatri & Brown (2010), data governance refers to what decisions must be made to ensure effective management and use of data (decision domains) and who makes the decisions (locus of accountability for decision making. For example, data governance includes establishing who in the organization holds decision rights for determining standards for data quality. Data Governance is discussed further in detail in section 3.7 below.

An AMDI, as CAS, "both reacts to and creates the environment it is operating in" (Choi et al., 2001, p. 355). In this way, an AMDI is inseparable from its environment. A CAS and its environment interact and create new realities. The environment forces changes in the CAS, which in turn induces changes in the environment. Choi et al. (2001) explain this phenomenon with the example of a team. As team members come closer together, they become more removed from their environments. The fitness a system can attain in the environment may be represented by a "landscape" in which possible states are represented by hills or peaks (Choi et al., 2001; Sherif & Xing, 2006). The highest point in this landscape may be considered the optimal state for the system. When individual components contribute in different ways, the optimal state becomes difficult to find (Choi et al., 2001). A system is a set of interrelated elements (Ackoff, 1971), and most systems are nested within other systems and many systems are systems of smaller systems (Janssen & Kuk, 2006). A system of systems is a collection of task-oriented systems that pool their resources and capabilities to create a new, more complex system which offers more functionality and performance than simply the sum of the constituent systems. While the individual systems constituting a system of systems can be very different and operate independently, their interactions typically expose and deliver important emergent properties (Gorod, Sauser, & Boardman, 2008).

### 3.7.2 Behaviors of AMDIs

CAS behavior *emerges* when many of its components interact. The whole of the system is different from the sum of its parts (Eoyang & Berkas, 1999) which means that CASs cannot be sufficiently analyzed by looking at components separately. The greater the variety within the system, the stronger it is (Janssen & Kuk, 2006). For example, combining data between multiple systems can create greater insights than simple analysis on single systems. CASs rely on ambiguity, paradox and contradictions to create new possibilities. The diversity of skills and strategies of agents

within an AMDI ensures its dynamic adaptive behavior (Rupert et al., 2008). For example, it is difficult for a single agent to evolve and become more useful in an isolated context (Sutherland & van den Heuvel, 2002). The relationships are complicated and massively entangled because the components are numerous and highly interrelated (Eoyang & Berkas, 1999). Also, AMDIs, just as many CASs, are driven by many interdependent variables, and behavior is often influenced by a wide variety of factors. Variables are often nonlinear and discontinuous, often having a changing level of influence over time. Non-linearity is the property in which there is a disproportionate response to change (Khouja et al., 2008; Rupert et al., 2008). As such, AMDIs, as CASs, are *dynamic*. Change in an AMDI is driven by the number of agents, their own rules of behavior and the interdependence between the agents and their environments (Eoyang & Berkas, 1999; Rupert et al., 2008). According to Choi et al. (2001), a complex system will balance between order and disorder. This balance point allows the system to maintain order while also reacting to changes in the environment. Once an AMDI reaches the state of being good enough, it will trade off efficiency with greater effectiveness (Janssen & Kuk, 2006).

Evolution is "a process of change and agility for the whole system" (Haghnevis & Askin, 2012, p. 520). In a CAS, agents are interconnected so that the behavior of an agent is influenced by the behavior of other agents in the system. As one agent evolves, so does the other (Haghnevis & Askin, 2012). This process is often referred to as "co-evolution" (Choi et al., 2001; Furneaux et al., 2008; Janssen et al., 2009). At a macro-level, AMDIs exist within their own environments, and they are also part of that environment. As their environments change, AMDIs need to change to ensure a good fit with their environments. However, as they change they also enforce changes in their own environments in a continuous, reciprocal process of evolution (Janssen et al., 2009). Adaptation can be described as change to the system which is the result of experience (Holland, 1992). CASs are capable of adjusting to external influences (Cilliers, 2002; Grus et al., 2010; Rotmans & Loorbach, 2009) and an AMDI will change constantly because of the continuous interactions and interdependence between its agents and its environment (Rupert et al., 2008).

Behavior in an AMDI is influenced by the simultaneous and parallel actions of agents within the system, causing behaviors to emerge. In other words, new structures, patterns, and properties arise without being externally imposed on the system (Choi et al., 2001; Hanseth & Lyytinen, 2010; Janssen et al., 2009). In this regard, macroscopic properties of an

AMDI arise from the heterogeneity of its elements and its relevant properties (Merali, 2006). The system displays a set of properties that is distinct from those displayed by any subset of its elements.

Aggregation is the behavior by which agents form groups that in turn can recombine to a higher level leading to the complex system (Rupert et al., 2008) - it is the basis for identity (Bollinger & Dijkema, 2012; Brown et al., 2011; de Man, 2006). According to Sutherland & van den Heuvel (2002), there are two important modes of aggregation in AMDIs: (1) objects and (2) components. Forming components from objects and forming systems from components is higher-level aggregation. Meta-agents such as an enterprise, are formed of aggregates of lower agents such as systems which are formed of aggregates of components, which are formed of aggregates of objects (Sutherland & van den Heuvel, 2002). Cilliers (2002) defines self-organization as a process whereby systems develop complex structures from simple beginnings under the influence of the external environment and the intrinsic "memory" of the system (Grus et al., 2010). Agents, learn and adapt to actions of other agents (Albino, Carbonara, & Giannoccaro, 2005) which results in the structure and dynamics of an AMDI (Furneaux et al., 2008). In an AMDI, there is often no centralized control mechanism, and order emerges as agents develop own rules as suggested by Rupert et al. (2008). Formal order is not externally imposed from outside of the AMDI, but rather emerges from interactions between agents (Stacey, 1995). In this regard, AMDI models are inherently multi-level as the order is seen as an emergent property which results from lower levels of aggregate behavior as suggested by (Anderson, 1999).

### 3.7.3 Conclusions

This literature review provides a new insight into the characteristics of AMDIs as CAS. Key components of AMDIs are data, agents, technology. The schema, which we have been able to identify as data governance, defines the "rules of the game", which defines how components interact. Part of this schema is how components of AMDIs can be coordinated. Coordination can be accomplished by mechanisms including self-organization, coordination by feedback, coordination by plan (direct supervision; mutual adjustment; standardization) and contracting for allocation of resources. The environment(s) in which the AMDI finds itself also impacts how elements interact and how AMDIs develop. As such, we can see that AMDIs are dynamic. They evolve and adapt to changing environmental factors and requirements. Furthermore, the degree of complexity of AMDIs can result in a massive number of objectives and

constraints causing over-specification, which precludes a realistic design. Therefore, it is important to define and delineate the AMDI as best as possible in order to be able to develop a workable model. Essentially, the ambition of the AMDI model will be to map the AMDI into the various functions, objectives and constraints as suggested by (Weijnen et al., 2008).

## 3.8 Towards Elements of Data Governance in Asset Management

As discussed in section 3.6, we identify data governance as embodying the *schema* of AMDIs. As such, data governance defines how the components of AMDIs (data, technology, agents) interact. But, as yet, little is known of data governance in asset management. Asset management organizations are facing increasing challenges to the management of their infrastructure assets (like banks, roads, and bridges), technological advances, political shifts, changing stakeholders, or economic fluctuations. Many asset management organizations routinely store large volumes of data in an attempt to find ways to improve efficiency and effectiveness of their AM processes through data-driven decision-making (Brynjolfsson, Hitt, & Kim, 2011; Dimitris Bertsimas & Aurélie Thiele, 2006). However, many organizations find it difficult to manage their data. Thompson (2011) believe that these difficulties may often be attributed to the lack of data governance. Therefore we need to understand what data governance is and what design principles should be followed when designing AMDI models. In this way, this section helps us answer Research Question 3.

Data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data (Khatri & Brown, 2010), ensures that data is aligned to the needs of the organization (Dawes, 2010), monitors and enforces compliancy to policy (Thompson et al., 2015), and ensures a common understanding of the data throughout the organization (Otto, 2011b). New sources of data, originating from sources such as social media and IoT, can provide new insights to help organizations face these challenges. But data must be of sufficient quality in order to be acted upon (Otto, 2013; Wende, 2007) and too much data can create "noise" which detracts van the quality of the information. A widely adopted definition of high quality data is data that is "fit-for-use" (Strong et al., 1997; Wende & Otto, 2007). Using the definition provided by Strong et al. (1997), the characteristics of high-quality data have intrinsic, accessibility, contextual, and representational

aspects. This also means that usefulness and usability are important aspects of quality (Dawes, 2010; Strong et al., 1997). Having AMDIs which produce data of a quality that is aligned to the needs of the organization is therefore essential for asset management organizations which rely on data-driven decision-making processes (Al-Khouri, 2012).

However, design principles for implementing and operationalizing data governance in asset management organizations are missing, and many organizations are struggling with the coordination of their data management activities. This section fills this gap by systematically investigating concepts related to asset management data governance and defines characteristics of data governance in asset management organizations. According to Otto (2011c), data governance aims at maximizing the value of data assets in enterprises. When IoT data is governed in order to meet business needs, the value obtained by the organization is amplified and revenue is increased (Malik, 2013). For example, smart meters, capturing electric- and gas-usage data every few minutes benefits the consumer as well as the provider of energy. IoT allows utility companies to intelligently match supply with demand and offer consumers incentives to change usage patterns and behaviors. With active governance of IoT data, isolation of faults and quick fixing of issues can prevent systemic energy grid collapse (Malik, 2013). According to Otto (2011a), the main business goals of data governance are to ensure compliance, enable decision-making, improve customer satisfaction, increase operational efficiency, and support business integration. Improving operational efficiencies and reduction of direct and indirect costs is of interest to managers across industries (Tallon, 2013). Table 3-5 below summarizes the main organizational goals of data governance.

Table 3-5: Organizational goals of data governance

| **Goal** | **Literature Examples** |
|---|---|
| Increase revenue | (Brous & Janssen, 2015b; D. Otto, 2011; Tallon, 2013) |
| Increase value | (Malik, 2013; Otto, 2011a; D. Otto, 2011) |
| Reduce cost | (Brous & Janssen, 2015b; Malik, 2013; Tallon, 2013) |
| Reduce complexity | (Malik, 2013; D. Otto, 2011) |
| Reduce risk | (Malik, 2013; Otto, 2011a; D. Otto, 2011; Tallon, 2013) |
| Ensure compliance | (Brous & Janssen, 2015b; Malik, 2013; Otto, 2011a) |
| Enable decision-making | (Brous & Janssen, 2015b; Otto, 2011a) |

| Goal | Literature Examples |
|---|---|
| Improve confidence | (Brous & Janssen, 2015b; Otto, 2011a) |
| Improve operational effectiveness | (Brous & Janssen, 2015b; Otto, 2011a) |
| Improve operational efficiency | (Brous & Janssen, 2015b; Malik, 2013; Otto, 2011a) |

IoT can provide continuous data emitted by embedded environmental sensors, and the monitoring and analysis of this data can provide insights for infrastructure managers into possible operational improvements and reduction of waste (Malik, 2013). Malik (2013) also suggests that alternative goals of data governance of IoT data are to help manage complexity and support risk management and compliance efforts. According to Brous & Janssen (2015b), governing IoT data can also promote confidence and improve the effectiveness and flexibility of service provision.

### 3.8.1 Concepts of Data Governance in Asset Management

This research follows the method of principle derivation recommended by Bharosa & Janssen (2015). Data governance principles are a set of statements that describe the basic doctrines of data governance (Dyché, 2007). This paper follows the definition of Bharosa & Janssen (2015, p. 472) who define principles as "normative, reusable and directive guidelines, formulated towards taking action by the information system architects". In their Architecture Framework (TOGAF), The Open Group lists five criteria that distinguish a good set of architecture principles: understandable, robust, complete, consistent and stable. Van Bommel, Hoppenbrouwers, Proper, & van der Weide (2006) believe that the underlying tenets should be quickly understood by individuals throughout the organization and according to Khatri & Brown (2010), principles should be supported by a rationale and a set of implications. A robust principle should enable good quality decisions to be made, and enforceable policies and standards to be created. According to The Open Group, architecture principles define the underlying general rules and guidelines for the use and deployment of resources and infrastructures across the enterprise. They should be consistent among the various elements of the enterprise, and form the basis for making future decisions, as opposed to requirements which are in natural conflict with all other requirements in their attempt to claim common resources (Gilb,

1997). Principles should be designed to capture prescriptive and directive guidelines that can be used to design systems within the framework of requirements and constraints (Bharosa & Janssen, 2015). As such, principles may be used to define a framework for coordination of activities (Crowston, 1997).

Following Bharosa & Janssen (2015), we started with identifying a long list of data governance dimensions in literature. The literature review follows the concept-centric methodology proposed by Webster & Watson (2002). As the review is concept-centric, the sources were grouped according to concept. Webster & Watson (2002) recommend the compilation of a concept matrix as each article is read. This concept-matrix is depicted below in Table 3-6.

Table 3-6: Long list of data governance key concepts

| Concept | Literature examples |
|---|---|
| Accountability | (Felici, Jaatun, Kosta, & Wainwright, 2013; Kim et al., 2014; Thompson et al., 2015) |
| Decision rights | (Otto, 2011a; Smallwood, 2014; Thompson et al., 2015; Wende & Otto, 2007) |
| Balanced roles | (Al-Khouri, 2012; Hripcsak et al., 2014; Smallwood, 2014) |
| Stewardship | (Dawes, 2010; Hripcsak et al., 2014; Thompson et al., 2015) |
| Ownership | (Griffin, 2010; Thompson et al., 2015; Tupper, 2011) |
| Separation of duties | (Malik, 2013) |

| Concept | Literature Examples |
|---|---|
| Compliance | (Al-Khouri, 2012; Alofaysan, Alhaqbani, Alseghayyir, & Omar, 2014; Smallwood, 2014; Thompson et al., 2015) |
| Policy enforcement | (Power & Trope, 2006; Tallon, 2013; Trope, Power, Polley, & Morley, 2007) |
| Due diligence | (Bruening & Waterman, 2010; Hripcsak et al., 2014; Smallwood, 2014) |
| Openness | (Felici et al., 2013; Kim et al., 2014) |
| Security | (Felici & Pearson, 2015; Hripcsak et al., 2014; Kim et al., 2014) |
| Measuring data quality | (Hripcsak et al., 2014; Khatri & |

| Concept | Literature examples |
|---|---|
| | |
| Separation of concern | (Malik, 2013) |
| Improved coordination of decision making | (Otto, 2011b; Smallwood, 2014; Tallon, 2013) |
| Meeting business needs | (Alofaysan et al., 2014; Dawes, 2010) |
| Aligning business and IT | (Panian, 2010) |
| Developing data strategy | (Khatri & Brown, 2010; Malik, 2013; Otto, 2011b; Tallon, 2013) |
| Defining data quality | (Alofaysan et al., 2014; Hripcsak et al., 2014; Kim et al., 2014) |
| Reducing error of use | (Coleman et al., 2009; Otto, 2013; Wende & Otto, 2007) |
| Effective policies and procedures | (Griffin, 2010; Hripcsak et al., 2014; Smallwood, 2014; Wende, 2007) |

| Concept | Literature Examples |
|---|---|
| | Brown, 2010; Kim et al., 2014) |
| Privacy | (Al-Khouri, 2012; Coleman, Hughes, & Perry, 2009; Felici et al., 2013) |
| Shared data commons | (Al-Khouri, 2012; Coleman et al., 2009; Otto, 2011b, 2013; Tallon, 2013) |
| Use of standards | (Otto, 2011b; Thompson et al., 2015) |
| Metadata management | (Khatri & Brown, 2010; Otto, 2011b) |
| Standardized data models | (Otto, 2011b; Thompson et al., 2015) |
| Standardized operational processes | (Otto, 2011b; Thompson et al., 2015) |
| Facilitates communication | (Malik, 2013; Otto, 2011b; Tallon, 2013) |
| | |

Following the recommendations of Bharosa & Janssen (2015) for principle generation, the long list of concepts seen in Table 3-6 was reduced to a short list as seen below in Table 3-7. The articles were categorized based on the types of variables examined, a scheme that helps to define the topic area.

Table 3-7: Concept matrix showing the elements of data governance in asset management in relation to goals and key concepts

| **Elements of Data Governance** | **Goals** | **Key Concepts** |
|---|---|---|
| Organizational Capability | Improve operational effectiveness<br>Enable decision-making | Decision rights<br>Balanced Roles<br>Stewardship<br>Separation of duties and concern<br>Improved coordination of decision making |
| Alignment | Increase revenue<br>Increase value<br>Reduce cost | Meeting business needs<br>Aligning business and IT<br>Developing data strategy<br>Defining data quality requirements<br>Reducing error of use<br>Effective policies and procedures |
| Clarification | Reduce complexity<br>Improve operational efficiency | Shared data commons<br>Use of standards<br>Metadata management<br>Standardized data models<br>Standardized operational processes<br>Facilitates communication |
| Compliance | Reduce risk<br>Ensure compliance<br>Improve confidence | Accountability<br>Policy enforcement<br>Due diligence<br>Privacy<br>Openness<br>Security<br>Data quality monitoring |

By focusing on the formal goals of data governance which we identified as independent variables, we could identify the dependent variables which we defined as the long list of concepts in Table 3-6. We grouped the long list of key concepts according to intervening variables which we identified as the short list of principles which appear in more complex causal relationships. As shown in Figure 3-5 below, four elements related to the goals of data governance were identified in the literature, namely: organizational capability, alignment, clarification and compliance.

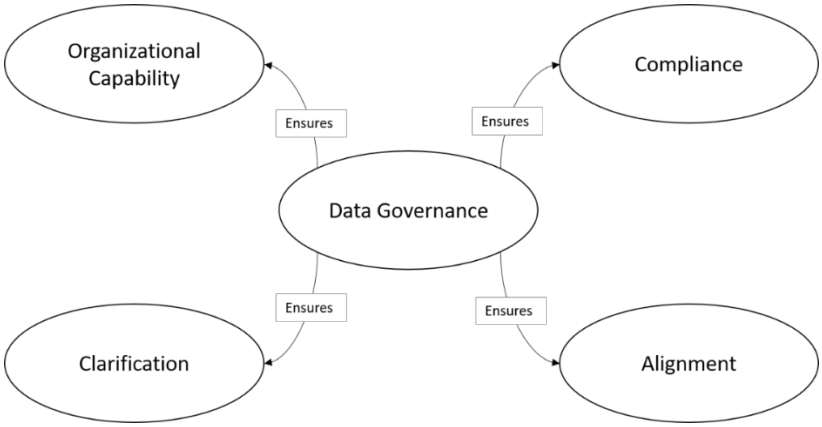


Figure 3-5: Concepts of Data Governance in Asset Management

The following sections discuss the short list of data governance principles as described in the literature from a coordination theory perspective. We begin the discussion with the concept, "Organizational capability", as this is traditionally the approach taken by most researchers and practitioners. But it is insufficient to only describe roles and responsibilities, as many organizations remain unaware of the task and activities that need to be performed by these roles. Therefore we continue the discussion with the concept, "Alignment", which describes how data governance should ensure that data meets the needs of the asset management organization. But there is often a tension between meeting the needs of the organization and ensuring compliance to laws and regulations. As such the third element we discuss is that of "Compliance". Yet all of the above elements can only apply if the organization is aware of what they have and how the data landscape appears. As such, we conclude the discussion with the element, "Clarification", as data governance should ensure that the organization has a common understanding of the data in its possession and a clear view of its data landscape.

### 3.8.2 Organizational Capability

Many researchers agree that data governance has an organizational dimension (Khatri & Brown, 2010; Otto, 2013; Wende & Otto, 2007). For example, Wende & Otto (2007) believe that data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data. The first organizational dimension of Otto (2013) relates to an organization's goals. Formal goals measure an

organization's performance and relate to maintaining or raising the value of a company's data infrastructures (Otto, 2013). Functional goals refer to the tasks an organization has to fulfil and are represented by the decision rights defined such as the definition of data quality metrics, the specification of metadata, or the design of a data architecture and a data lifecycle (Weber, Otto, & Österle, 2009). Otto's (2013) second organizational dimension is the organizational form, such as the structure in which responsibilities are specified and assigned, and the process organization. Issues are addressed within corporate structures (Wende & Otto, 2007). The data governance model is comprised of roles, decision areas, main activities, and responsibilities (Wende & Otto, 2007). However, the organization of data governance should not be seen as a "one size fits all" approach (Wende & Otto, 2007). Decision-making bodies need to be identified for each organization, and data governance must be institutionalized through a formal organizational structure that fits with a specific organization (Malik, 2013). Decision rights indicate who arbitrates and who makes those decisions (Dyché, 2007). According to Dawes (2010), "stewardship" focuses on assuring accuracy, validity, security, management, and preservation of information holdings.

In the past, organizations have generally tended to assign accountabilities for data mostly to IT departments (Wende & Otto, 2007). Organizations have thereby ignored critical organizational issues (Wende & Otto, 2007). Data governance is a complex undertaking and many data governance initiatives in public organizations have failed in the past. As such, the organization of data governance should not be a "one size fits all" approach and data governance must be institutionalized through a formal organizational structure that fits with a specific organization. Data governance should also ensure that data is aligned with the needs of the business. This includes ensuring that data meets the necessary quality requirements. Ensuring alignment can take the form of defining, monitoring and enforcing data policies (internal and external) throughout the organization. Establishing and enforcing policies regarding the management of data is important for an effective data governance practice. According to Dawes (2010), policies reflect societal choices about how data should be handled. Policies reflect strong values attached to data sources and content as well as access to and participation in the marketplace of ideas. By applying principles, an organization treats data as an object of policy, that is, data itself is the subject of policy making (Dawes, 2010). Policy provides broad general guidance and helps to regulate data processes. But governing data appropriately is only possible if it is properly understood what the data to be managed means, and why

it is important to the organization (Brous, Herder, & Janssen, 2016). The wide variety of data formats, protocols and data types drive the need for interoperability through standardization. Standards are "an agreed upon set of rules that are established by an authority" (Mathew, Ma, & Hargreaves, 2008, p. 3). Despite the plethora of standards, many researchers (Grus et al., 2010; Mathew et al., 2008; Rajabifard et al., 2002) believe that they play an important role in data infrastructures. The endorsement of standards allows them to be widely implemented, improving interoperability and supporting the data process. Within the data management process, knowledge about work processes encompasses knowledge about the key processes within the data management process: collection of raw data, storage and maintenance of data, and user retrieval and manipulation of data (Ballou, Madnick, & Wang, 2003; Strong et al., 1997; Wang, Lee, Pipino, & Strong, 1998). Knowledge about work performance is knowledge about producing high-quality data from data production processes.

Otto's (2013) third organizational dimension consists of a transformation process on the one hand and organizational change measures on the other. As such, mutual adjustment and standardization become important organizational coordination mechanisms (Mintzberg, 1993). Malik (2013) indicates the need to establish clear communications and patterns that would aid in handling policies for quick resolution of issues, and Thompson et al. (2015) show that coordination of decision making in data governance structures may be seen as a hierarchical arrangement in which superiors delegate and communicate their wishes to their subordinates, who in turn delegate their control. But Grus et al. (2010) believe that competition in the sector may force organizations to change their organizational models.

### 3.8.3 Alignment

Data governance should ensure that data meets the needs of the business (Panian, 2010). A data governance program must be able to demonstrate business value, or it may not get the executive sponsorship and funding it needs to move forward (Smallwood, 2014). Describing the business uses of data establishes the extent to which specific policies are appropriate for data management. According to Panian (2010), if used correctly, data can be a reusable infrastructure as data is a virtual representation of an organization's activities and transactions and its outcomes and results. Data governance should ensure that data is "useful" (Dawes, 2010). According to Dawes (2010), information should be helpful to its intended users, or should support the usefulness of other

disseminated information. However, while asset management organizations may want to achieve the goals of data governance in theory, they often have difficulty justifying the effort unless it has a practical, concrete impact on the business (Panian, 2010). Data governance also provides the framework for addressing complex issues such as improving data quality or developing a single view of the customer at an enterprise level (Panian, 2010). Wende & Otto (2007) believe that a data quality strategy is therefore required to ensure that data management activities are in line with the overall business strategy. The strategy should include the strategic objectives which are pursued by data quality management and how it is aligned with the company's strategic business goals and overall functional scope. Data quality is considered by many researchers to be an important metric for the performance of data governance (Khatri & Brown, 2010; Otto, 2011b; Wende & Otto, 2007).

### 3.8.4 Compliance

Data governance includes a clearly defined authority to create and enforce data policies and procedures (Wilbanks & Lehman, 2012). Panian (2010) states that establishing and enforcing policies and processes around the management data is the foundation of an effective data governance practice. Delineating the business uses of data, data principles establish the extent to which data is an enterprise wide infrastructure, and thus what specific policies are appropriate (Khatri & Brown, 2010). According to Malik (2013), determination of policies for governance is typically done in a collaborative manner with IT and business teams coming together to agree on a framework of policies which are applicable across the whole organization. Tallon (2013) regards data governance practices as having a social and, in some cases, legal responsibility to safeguard personal data through processes such as "privacy by design", whilst Power & Trope (2006, p. 471) suggest that risks and threats to data and privacy require diligent attention from organizations to prevent "bad things happening to good companies and good personnel". Mechanisms need to be established to ensure organizations are held accountable for these obligations through a combination of incentives and penalties (Al-Khouri, 2012) as, according to Felici et al. (2013), governance is the process by which accountability is implemented. In such a manner, accountability can unlock further potential by addressing relevant problems of data stewardship and data protection in emerging in data ecosystems. According to Winograd & Flores (1986), most human coordination occurs in a cycle of requesting, making and fulfilling commitments between people. John (1962) believes that most things that people say are not simply propositions of truth or

falsehood, but are attempts by the speaker to do something. The change in status through commitments and formations of new identities are often overlooked and we are often surprised by new social institutions and identities when they arise such as the working together of teams in which the components look the same as in previous friendships, but where new commitments implicitly rule. Changing commitments may have a significant impact on the interaction of elements within data infrastructures.

### 3.8.5 Clarification

According to Smith (2007), governing data appropriately is only possible if it is properly understood what the data to be managed means, and why it is important to the organization. Data understanding is essential to any application development, data warehousing or services-oriented-architecture effort. Misunderstood data or incomplete data requirements can affect the successful outcome of any IT project (Smith, 2007). Smith (2007) believes that the best way to avoid problems created by misunderstanding the data, is to create an enterprise data model (EDM) and that creating and developing an EDM should be one of the basic activities of data governance. Attention to business areas and enterprise entities should be the responsibility of the appropriate data stewards who will have the entity-level knowledge necessary for development of the entities under their stewardship (Smith, 2007). To ensure that the data is interpretable, metadata should be standardized to provide the ability to effectively use and track information (Khatri & Brown, 2010). This is because the way an organization conducts business, and its data, changes as the environment for a business changes. As such, Khatri & Brown (2010) believe that there is a need to manage changes in metadata as well. Data governance principles should therefore reflect and preserve the value to society from the sharing and analysis of anonymized datasets as a collective resource (Al-Khouri, 2012). Coordination manages dependencies between activities (Malone & Crowston, 1990). These dependencies arise from the mutual use of common objects to carry out a task (Malone & Crowston, 1990). Thus, communication is necessary for coordinating processes. For instance, actors performing interdependent activities may have conflicting interests. Political processes are ways of managing them. This perspective is upheld by the view that coordination is the management of dependencies between decision processes that allocate scarce resources among actors.

## 3.9 Summary of Chapter 3

Currently, organizations are experimenting with new data sources and there is a general expectation that IoT will provide significant added value to AM decision making. Organizations can effectively and sustainably adopt these new data sources in their AM decision making if the data that is measured can monitor the important factors of the asset itself. However, although IoT provides many benefits the use of the technology is a product of human actions and these actions determine the actual benefits to be gained.

The literature review answers, in part, *Research Question 1* by providing a systematic insight into the uses of IoT in asset management and the expected and achieved benefits of IoT for asset management organizations. Table 3-8 below summarizes how IoT adoption may change asset management, answering, in part, research question 1.

Table 3-8: Summary of how IoT adoption can change asset management

| **Uses of IoT in Asset Management** | **Improvements to Asset Management** |
|---|---|
| IoT data expected to change performance measurement of infrastructure service | Improved forecasting and trend analysis |
| IoT data expected to change perception of infrastructure service | Improved transparency<br>Improved citizen empowerment |
| IoT data expected to change improvement processes of infrastructure service | Improved planning with regards to management and maintenance<br>More efficient regulations<br>More efficient enforcement of regulations<br>Reduction of costs<br>New revenue streams<br>Improved efficiency of services<br>Improved effectiveness of services<br>Improved flexibility of services |

The literature review shows that expected benefits range from the strategic to the operational level. Specifically benefits can be attributed to improved efficiency, effectiveness and flexibility of services; reduction of costs; improved citizen empowerment; improved organizational transparency; more efficient enforcement of regulations; improved planning and forecasting; and improved health and safety measures. But there may also be risks to the asset management organization that can go beyond the accomplishment of the intended benefits. Specifically risks can be attributed to data privacy issues, data security issues, weak or

uncoordinated data policies, weak or uncoordinated data governance, and conflicting market forces, costs, interoperability and integration issues, acceptance of IoT, and trust related issues, a lack of sufficient knowledge regarding IoT, IT infrastructural limitations, and data management issues. It is clear that IoT will have a major impact on asset management in the future and will bring a variety of benefits at all levels, but IoT adoption can have unforeseen social risks for the organization which go beyond the intended. Many of the issues which occur are interrelated; for example, interoperability and integration issues have a direct impact on costs and on trust in the systems, but many issues can also be resolved with sufficient knowledge and capabilities within the organization.

In this research elements of AMDIs are viewed from a CAS perspective. In this way, the literature review goes some way to helping us answer *Research Questions 2, and 3*. As seen in Table 3-9 below, AMDIs consist of *components* (Haghnevis & Askin, 2012), which are embodied by data, technology and agents. A*gents* (Janssen & Verbraeck, 2005) interact with one another within a certain *schema* (Choi et al., 2001). Schema refers to shared rules which are embodied by norms, values, beliefs, and assumptions. In this research we identify the schema within which agents interact as being embodied by data governance. Theoretically, data governance describes the processes, and defines responsibilities. Data managers then work within this framework. Four key elements of data governance were identified during the literature review: 1. Organizational capability; 2. Alignment; 3. Compliance; 4. Clarification. Table 3-9 below shows the elements of AMDIs, answering, in part, Research Questions 2 and 3.

Table 3-9: Summary of the elements of AMDIs as CAS

| **Elements of AMDIs** | | | |
|---|---|---|---|
| **Components** | **Agents** | **Schema – Data Governance** | **Environments** |
| Data<br>Technology<br>People | Individuals<br>Teams<br>Departments<br>Divisions<br>Organizations | Organizational capability<br>Alignment<br>Compliance<br>Clarification | Physical asset infrastructure<br>Organizational culture<br>Organizational structure<br>Political/legal environment |

AMDI behavior *emerges* because many of the simple components interact simultaneously. The whole of the system is different from the sum of its parts which means that AMDIs cannot be adequately analyzed by examining their parts separately. Furthermore, AMDIs, as CASs, are *dynamic*, and because of the number of agents, their interdependence, and their openness to external influences, changes constantly and discontinuously. AMDIs are able to *adapt* to external influences and an AMDI will change constantly because of the continuous interactions and interdependence between its agents and its environment. In an AMDI, there is often no centralized control that dictates the system's overall behavior. Order emerges as agents govern their own rules of behavior and adapt to their environment. According to Janssen et al. (2009), AMDIs display *connectivity* as the ways agents in AMDIs connect and relate to each other is critical to understanding the system. Table 3-10 below summarizes the behaviors of AMDIs, partly answering research question 2.

Table 3-10: Summary of the behaviors of AMDIs CAS

| **Behaviors of AMDIs** | | | |
|---|---|---|---|
| **Dynamism** | **Emergence** | **Adaptation** | **Connectivity** |
| In constant development (i.e. addition of IoT sensors to the network, or changes to data models)<br>Complicated and entangled relationships (i.e. large numbers of data integrations, and difficult to define data ownership) | Combining data between systems creates greater insights than analysis on single systems.<br>Constant exchange of information and needs leading to emerging capabilities<br>Aggregation of objects and components<br>Order emerges through agent interaction | Adaption in use of systems due to continuous interactions and interdependence between agents and environment<br>Adaptations in AMDI structure due to experience<br>Adaptations in structure due to changes in environment<br>Adaptations in environment due to changes in the AMDI | Integration of multiple systems (system of systems)<br>Connectivity between objects and agents<br>Interaction between agents<br>Data integration between disjointed systems |

In Chapter 4 the results of the exploratory cases are presented from three architectural viewpoints. The literature review directs the exploratory cases as real world IoT implementations are examined in order to understand: how, and if, theoretical, expected, benefits of IoT

are achieved by asset management organizations; how the AMDIs have been structured and how the AMDIs have adapted to the new techniques; and how the asset management organizations leverage data governance to coordinate changes to the AMDI.

# Chapter 4 Exploratory Case Studies

*"All his faults observed,*
*Set in a note-book, learn'd, and conn'd by rote."*
**- William Shakespeare (*Julius Caesar, Act-IV, Scene-III*)**

## 4.1 Introduction

In Chapter 3 we discussed, by means of a systematic literature review, the dual nature of asset management through IoT and the necessity of viewing AMDIs as CAS when adopting IoT in asset management. The literature review showed that IoT has many benefits for asset management, but often introduces unexpected changes and risks to the organization which need to be mitigated. This provided us with a knowledge base on which we are able to build our theory that a model of AMDIs can improve understanding of asset management through IoT, provide actionable insights and predict previously unforeseen changes to asset management organizations when adopting IoT. The literature review also reveals gaps in our knowledge base which we attempt to fill in this Chapter by means of exploratory case studies. For example, little research is available regarding data governance in an asset management setting and it is unclear what data governance in asset management entails.

Due to the limited amount of scientific knowledge with regard to AMDIs and asset management through IoT, the initial case studies are of an exploratory nature and aim at laying the foundation for pertinent propositions for further inquiry. In exploratory cases, Yin (2009) concedes that no elaborated propositions can be specified beforehand, but instead suggests that case studies be purpose-oriented, with a preliminary conceptual framework guiding the exploration. As such, the explanatory cases outlined in this research rely on two main theories, Duality of Technology theory and CAS theory respectively, as conceptual frameworks.

A single, comprehensive model is often too complex to be understood and communicated in its most detailed form, showing all the relationships between the various business and technical components. We need to represent the AMDI in a way that is manageable and comprehensible for a range of business and technical stakeholders. A widely used approach is to partition the architecture into a number of separate but interrelated views, each of which describes a separate aspect of the architecture. Collectively, the views describe the whole system. According to The Open Group, architecture views are representations of the overall architecture that are meaningful to one or more stakeholders in the system which help to verify that the system will address their concerns. In this research we investigate the AMDI by assessing the case studies using three views, namely:

1. From a practice perspective: IoT provides benefits for asset management, but also introduces unexpected risks which impacts the organization and, in turn, the technology itself.
2. From a CAS perspective: AMDIs are complex systems composed of elements and behaviors which need to be identified.
3. From a data governance perspective: AMDIs follow rules according to a schema which we identify as data governance.

According to the Open Group (accessed 2017: http://www.opengroup.org/public/arch/p4/views/vus_intro.htm), a view is specified by means of a viewpoint, which prescribes the concepts, models, analysis techniques, and visualizations that are provided by the view. A view is what you see, and a viewpoint is where you are looking from. A viewpoint is a collection of patterns for constructing one type of view. It defines the guidelines, and principles for constructing its views. An architect is confronted with many different types of stakeholders and concerns and often bases the viewpoint on purpose and content. In this research, the initial case studies are of an exploratory nature and aim at laying the foundation for pertinent propositions. We therefore choose an overview abstraction level based on the introductory viewpoint. The exploratory cases are used to generate the initial theory which, following the design science framework is used to define requirements and build the artefact, in this research the AMDI model. Duality of Technology theory and CAS are used to develop a framework of views for guiding the exploratory case studies, as seen below in Figure 4-1.

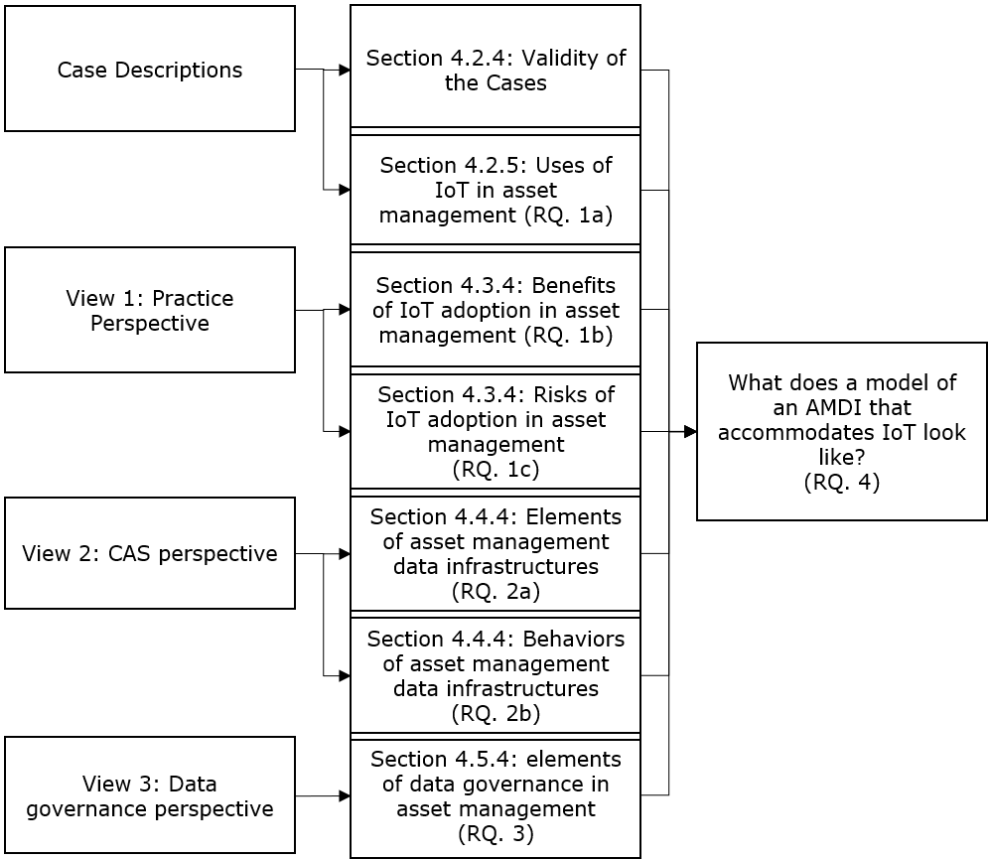


Figure 4-1: Relationship of the Views to the Research Questions

Duality of Technology theory is used to guide the investigation into the effects of asset management through IoT. In this research we take the introductory (purpose), overview (content) viewpoint. This means that we summarize the business, application and technology layers with the purpose of making design choices visible. The reader should note that parts of this chapter have been published in: Brous, Janssen, Herder, (2018) "Internet of Things adoption for reconfiguring decision-making processes in asset management", Business Process Management Journal, https://doi.org/10.1108/BPMJ-11-2017-0328.

*Duality of Technology: Overview*

Duality of technology (Orlikowski, 1992) describes technology as assuming structural properties whilst being the product of human action.

As such, technology is created by actors in a social context, and socially constructed by actors by attaching different meanings to it, and thus, technology results from the ongoing interaction of human choices and institutional contexts (Orlikowski, 1992). Orlikowski (1992) explains that previous research studies in the fields of technology and organizations have focused on the views that technology is either an objective, external force that has a deterministic impact on organizational properties such as structure, or that human action is an aspect of technology whereby technology is an outcome of strategic choice and social action. Orlikowski (1992) suggests that both models are incomplete, and proposes a reconceptualization of technology that takes both perspectives into account, proposing a structuration model of technology by exploring the relationship between technology and organizations, based on Giddens' (1976), "Theory of Structuration". Giddens (1976) recognizes that "human actions are both enabled and constrained by structures, yet that these structures are the results of previous actions" (Orlikowski, 1992, p.404).

Orlikowski (1992) identifies technology as being the product of human action, while it also assumes structural properties. Furthermore, technology is physically constructed by actors working in a given social context and socially constructed by actors through the different meaning they attach to it. According to Orlikowski (1992), understanding technology as continually being socially and physically constructed requires discriminating between human activity which affects technology, and human activity which is affected by technology. Figure 4-2 below depicts the structural relationship between organizations, human agents and technology.

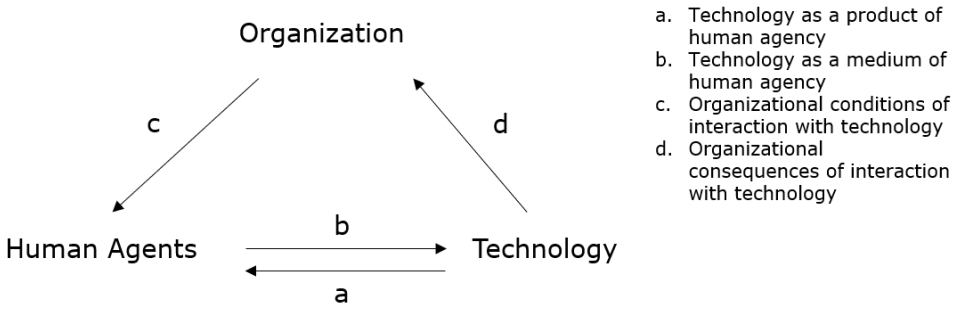


Figure 4-2: Structuration model of technology (Orlikowski, 1992)

Research in the sociology of technology suggests that the evolution of new applications is a process of social interaction between multiple agents (Allen, 2003). According to Orlikowski (1992), agency refers to capability not intentionality, and action taken by actors may have unintended consequences. Orlikowski (1992) premises that technology is created and changed by human action, however technology is also used by humans to accomplish some action, which is what Orlikowski (1992) calls the *Duality of Technology*. Orlikowski's (1992) second premise is that technology is interpretively flexible. However interaction of technology and organization is a function of the different actors and the socio-historical contexts implicated in its development and use. According to Leonardi (2013), the duality of technology model is important as a waypoint to Orlikowski's (2000) practice lens. Leonardi (2013) believes that, having already conceptualized technology use as a constitutive feature of structure in its own right, Orlikowski (2000) introduced the development of the practice lens, the "technology-in-practice," which Orlikowski (2000, p. 405) defined as "a particular structure of technology use". As such, Leonardi (2013) argues that the practice lens tends to hide patterns of technology use into particular "technologies-in-practice" as people tend to interpret how technology could help them achieve their goals. Leonardi (2013) also criticizes the practice lens for offering an overly socialized view of technology. Leonardi's (2013) critique is based on the idea that people choose to use technology in a certain way. As such, the technologies themselves "are only peripheral players that are subject to the whims of their users" (Leonardi, 2013, p. 64). By way of example, (Leonardi, 2013, p. 64) cites Orlikowski (2000) as arguing that that "even though technologies have certain physical or digital properties that transcend specific contexts of use, users have the option to choose other options with the technology at hand, opening up the potential for innovation, learning, and change". Leonardi (2013) argues that technology-in-practice is therefore only a set of norms governing when, why, and how to use a technology in a specific setting.

Duality of Technology Theory (Orlikowski, 1992) suggests that IoT adoption may provide operational, tactical and strategic benefits to the asset management organization which may trigger unexpected changes to the environments in which the AMDI operates. These changes may then, in turn, initiate new evolutions and adaptions to the AMDI which constrain the actions of asset managers. Also, changes to the asset management organization due to internal and external social constructs (such reorganizations of departments) or physical changes (such as a change in the organization's location) may force evolutions or adaptions

to the AMDI, which, in turn, may trigger further changes to the physical constructs of the asset management organization. This leads us to our first view which reads as follows:

**View 1.** Practice perspective: IoT provides benefits for asset management, but also introduces unexpected risks which impacts the organization and, in turn, the technology itself.

An AMDI, as CAS, both reacts to and creates the environment it is operating in. CAS theory as a framework is used as the logic which links the data from the exploratory case studies to the investigation into characteristics of AMDIs and the related data governance (schema), and serves as guidance for the interpretation of findings.

*CAS: Overview*

We are surrounded by complex worlds, composed of multitudes of elements, which make them hard to model and difficult to understand. Despite the plethora of examples used by researchers to describe what a CAS is, there appears to be little agreement as to an exact definition and what the characteristics of a CAS should be. For example, Wallis (2008) deconstructs twenty versions of CAS theory related to the management science discipline and concludes that the variety of definitions is result of the situation of the definitions in different research fields. In this research our focus is on data infrastructures. We follow Grus et al. (2010), whose research field is spatial data infrastructures, and we use the definition given by Barnes, Matka, & Sullivan (2003, p. 276) who define CASs as, "*open systems in which different elements interact dynamically to exchange information, self-organize and create many different feedback loops, relationships between causes and effects are nonlinear, and the systems as a whole have emergent properties that cannot be understood by reference to the component parts*".

Complexity arises when the dependencies among the elements become important. In such a system, removing one element destroys system behavior to a further extent than what may be expected. Complexity is therefore a deep property of the system (Miller & Page, 2009). A complex system will die when an essential element is removed. But despite this fragility, complex systems can also exhibit an unusual degree of robustness to less radical internal changes. The behavior of

many complex systems arises from the activities of lower-level components. This is the result of a very powerful organizing force that can overcome a variety of changes. But if the changes are too extreme, then the systems' behavior as we know it will collapse (Holland, 1992). This is particularly the case when there is a dependence on interactions between elements. The resulting anticipation can cause major changes in the behavior of the system, even when the anticipated situation does not arise. Because the individual parts of a complex adaptive system are continually revising their rules for interaction, each element is forced to adapt to the changing behavior of the other elements. In this way, CAS continue to evolve, and steadily exhibit new forms of emergent behavior. A complicating factor which contributes to the difficulty in defining characteristics of CASs is that characteristics can be divided into physical elements and behaviors. CAS elements are sets of system physicalities that together make CASs different from other systems. Similarly, CAS behaviors are the distinctive collection of functions and operations that make CAS behavior unique. Functional behavior being the behavior required to achieve a purpose and operational behavior being how the CAS achieves a purpose. As such, gaining useful information from IoT data for asset management purposes requires combining data registrations that have a sufficient level of quality with metadata that also has a sufficient level of quality. IoT adoption in asset management requires the interaction of agents across the strategic, tactical and operational levels. Also, Information Technology provides the capability of the AMDIs to perceive, process and transmit data and is an important enabler of IoT adoption in asset management. This leads us to our second view which reads as follows:

**View 2**. CAS perspective: AMDIs are complex systems composed of elements and behaviors which need to be identified.

Schema refers to shared rules which are embodied by norms, values, beliefs, and assumptions (Choi et al., 2001). The schema of AMDIs is embodied by data governance. Data governance organizes the management of IoT data and defines roles and responsibilities of agents in AMDIs. There is no "one-size-fits-all" approach to structuring data governance, and coordination of data management is often performed using formal and informal coordination mechanisms. Data governance aligns the supply of IoT data with the needs of asset managers and ensures that IoT data is useful to the asset management organization,

ensuring the provision of the right data to the right people at the right time. Data governance clarifies IoT data and ensures a shared view of the data throughout the asset management organization and across organizational silo's. Data governance also ensures compliance of IoT data with internal and external laws, regulations and policies affecting the asset management organization. This leads us to our third view which reads as follows:

**View 3.** Data governance perspective: AMDIs follow rules according to a schema which we identify as data governance.

Using the above views as starting points, the exploratory cases allow us insight into how AMDIs evolve and adapt to specific situations. The exploratory case studies focus specifically on asset management organizations in the water management domain. The following section begins with a short introduction to the cases under study. The introductions serve to introduce the context and develop the case introductions from chapter 2. The rest of the chapter reads as follows: first the cases are introduced one after the other, LMW (RWS), BOS (Water Authority Delfland), and Ground Water Measurement (Municipality of Rotterdam) respectively, then the next sections discuss each of the three views in turn, following the same format as the introduction: first discussing the national AMDI (LMW, RWS), then the regional AMDI (BOS, Water Authority Delfland), and then the local AMDI (Ground Water Measurement, Municipality of Rotterdam). At the end of each section the cases are compared according to the formats described at the beginning of each section.

## 4.2 Approach and General Descriptions

The exploratory cases were chosen as being representative of organizations at the national, regional and local levels respectively, in compliance with the principles outlined in Chapter 2. The structure of the exploratory case study descriptions in section 4.3 is as follows:

1. Stakeholder overview
2. IoT System overview
3. Asset management process before adoption
4. IoT system usage and asset management process after IoT adoption.

The various structures of each of the views are presented in the introduction of each section. The cases are described in the following order: National (RWS), Regional (Water Authority Delfland), and, finally, Local (Municipality of Rotterdam). At the end of the section, a comparison of the cases is provided.

The protocol used in the case studies includes a variety of data collection instruments. The use of multiple research instruments is encouraged to ensure construct validity through triangulation, made possible by multiple data collection methods which, as argued by (Eisenhardt, 1989), provide a stronger substantiation of our constructs and hypotheses. Triangulation means taking different angles towards the studied object, providing a broader picture and is important to increase the precision of empirical research (Runeson & Höst, 2008). At the start of the exploratory research, in June 2015, group discussions were held with personnel directly involved in the exploratory use cases or who were tasked with managing and maintain the systems. Special focus was given to expected and experienced benefits as well as expected risks. Between October 2015 and June 2017, individual interviews were held with personnel in the organizations under study. Internal documentation was selected which dealt with issues faced by the adopting projects. All interviews were documented in writing. The documents were then analyzed and transferred into an integrated case document (one for each case). The first versions of this document were then sent to the interview participants for feedback and clarification of open points. Once all the additional information feedback had been incorporated, the final version was reviewed and discussed with the main contacts at the organizations under study.

Table 4-1, Table 4-2, and Table 4-3 below give an overview of the sources used in the case studies.

Table 4-1: Data Sources of Case Study 1: National Water Measurement Network

| **Data Sources Type** | **Data Sources** |
|---|---|
| Interviews | June 2015: Group discussion<br>Department Head<br>Domain Architect<br>Service Delivery Manager<br>Data Manager |
| | October 2015: Individual Interviews |

| Data Sources Type | Data Sources |
|---|---|
| | Enterprise Architect<br>Senior Advisor LMW<br>Domain Architect Water Management<br>Domain Architect Shipping Management<br>Data Manager |
| | January 2017: Individual interviews<br>Strategic Advisor<br>Solution Architect<br>Process Manager<br>Project Manager<br>Service Delivery Manager |
| Documents | https://www.helpdeskwater.nl/onderwerpen/monitoring/landelijk-meetnet/<br>Evaluatie basismeetnet waterkwaliteit Hollands Noorderkwartier<br>Marktconsultatiedocument LMW2-V 1.1 DEF<br>Nota van Inlichtingen Marktconsultatie LMW2 V 1.0<br>Verslag Marktconsultatie LMW2-V1.0 DEF |

Table 4-2: Data Sources of Case Study 2: Decision Support System for Main Pumping Stations

| Data Sources Type | Data Sources |
|---|---|
| Interviews | June 2015 – June 2016:<br>Senior Policy Advisor Data Management<br>Project Manager Asset Management<br>Asset Data Manager<br>Manager Asset Management<br>Sector Head Policy and Communication<br>Manager Water Level Management |
| Documents | Waterbeheerplan 2016-2021 Delfland<br>Proeftuin Fysieke Digitale Delta<br>GEGEVENSBEHEER: 'Basis op orde' - Plan van Aanpak<br>KRW-programma Delfland 2016-2021<br>GEGEVENSBEHEERPLAN: (overkoepelend) - Van de gegevens over het Watersysteem en Waterkeringen<br>Smart Water Management Delfland<br>Ontwerp Waterbeheerplan 2016-2021<br>Functioneel ontwerp BOS 2.0<br>Hoofdlijnenakkoord Gegevensbeheer Watersysteem en Waterketen<br>Gegevensbeheer Watersysteem en Waterketen<br>Delft-FEWS Gebruikersdagen 14 juni 2016 |

Table 4-3: Data Sources of Case Study 3: Ground Water Measurement

| Data Sources Type | Data Sources |
|---|---|
| Interviews | October 2015:<br>Data Manager Base Information<br>Program Manager Stedelijk Beheer (City Management)<br>Enterprise Architect City Development<br>Project Manager IT<br>Asset Manager<br>Process Manager City Management<br>Manager Data Analysis |
| Documents | Gemeentelijk rioleringsplan: Planperiode 2016-2020<br>Waterplan 2 Rotterdam<br>Herijking Waterplan 2 Rotterdam<br>Maatregelen ter bestrijding van grondwateroverlast in bestaand stedelijk gebied<br>Organogram gemeente Rotterdam<br>Rotterdam en gebiedsgericht grondwaterbeheer<br>Uitvoeringsprogramma Water 2015 |

### 4.2.1 LMW - Rijkswaterstaat

The first case, the automatic measurement of hydrological data in Dutch Waters, is managed by the Directorate General of Public Works and Water Management of the Netherlands, commonly known within The Netherlands as “Rijkswaterstaat”. Rijkswaterstaat is often abbreviated to “RWS”, and is referred to as such within this research. RWS is part of the Dutch Ministry of Infrastructure and the Environment and is responsible for the design, construction, management and maintenance of the main infrastructure facilities in the Netherlands. This includes the main road network, the main waterway network and the main water systems of The Netherlands. The state road network constitutes three thousand kilometers of highways, one thousand four hundred km of connecting roads, two thousand seven hundred and forty-nine viaducts, thirteen ecoducts, twenty-two tunnels and seven hundred and forty-three bridges. Rijkswaterstaat is very active within information management in The Netherlands. They are, for example, responsible for the functional management of the national spatial data portals and the development of the maritime single window in The Netherlands. Rijkswaterstaat also produces and maintains a large amount of data and is a recognized authority on the management of large-scale physical infrastructure. The Netherlands has a long tradition of water management and, as an area, is essentially the most highly managed delta region in the world.

Traditional water level management was always performed by hand, sight or analogue based measurements in which the asset manager was forced to constantly read out the measurements by hand. As such, read outs were done during long intervals and then calculated by hand. Decision making was often based on experience. The conventional bathymetric data sets consist of measurements by means of sonar, photogrammetry and laser altimetry and measurements with the WESP (Water and Beach Profiler).

The main system currently used by RWS to manage their national water network is the National Water Measurement Network, at RWS known as "Landelijk Meetnet Water" (LMW). This is a facility that is responsible for the acquisition, storage and distribution of data for water resources. The LMW has a long and rich history and was created from the merging of three previous existing monitoring networks in the 1990's: the Water Monitoring Network, which monitors inland waterways such as canals and rivers; the Monitoring Network North, which monitors North Sea oil platforms and channels; and the Zeeland Tidal Waters Monitoring Network which monitors the Zeeland delta waterways. As such, LMW is about 25 years old but has experienced a number of upgrades in its current form, as recently as 2015, especially with regards to data transmission and data sharing. LMW has approximately 640 data collection points using a nationwide system of sensors. The data is then processed and stored in the data center and is made available to a variety of systems and users.

LMW also includes data from third parties, including water data from foreign countries and other public organizations within The Netherlands such as the shipping and transport industry, logistics, harbor management, meteorology, regional and local water management, and international water management. LMW has approximately 640 data collection points using a nationwide system of sensors. Figure 4-3 and Figure 4-4 below show examples of measuring stations used in the LMW network. The data is then processed and stored in the data center and is made available to a variety of systems and users.

Figure 4-3: LMW Measurement Station (RWS, 2017)

Figure 4-4: LMW Measurement Station (RWS, 2017)

Figure 4-5 below is a screen shot of the interactive water map of RWS in which different views of the data can be chosen and viewed across the Netherlands.

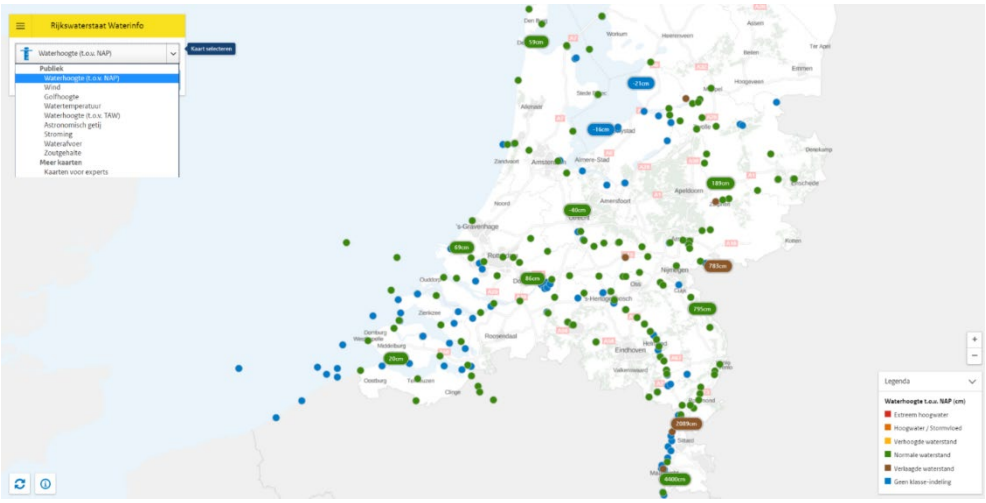


Figure 4-5: Screen shot of the RWS interactive water map

(https://waterinfo.rws.nl/#!/kaart/waterhoogte-t-o-v-nap/)

As seen in Figure 4-5 above, LMW collects data regarding water levels, wind speed, wave heights, water temperature, astronomical tides, water currents, salt content etc. This data is aggregated and calculated within models to accurately predict water levels and water quality. Based on these models, decisions are made to close storm surge barriers, close swimming areas, send out messages to shipping etc. As such, we can classify LMW services as being collaborative aware services (Gigli & Koo, 2011), as LMW services are used to make decisions, and based on those decisions, to perform an action. LMW services have "terminal-to-terminal" communication, as the Maeslant storm surge barrier is completely automated based on LMW data, as well as "terminal-to-person" communication as LMW data is distributed to multiple parties.

Measurements include hydrological and meteorological data. Meteorological data are collected in close collaboration with the Royal Netherlands Meteorological Institute (KNMI). Hydrological data is collected concerning the measurement of water levels, flow rate (average amount of water in m3/s), wave height and direction, velocity and direction and temperature. Also, in some locations water quality is

measured in order to assess whether the water meets the norms of the European Union Water Framework Directive. Meteorological data concerning the measurement of wind speed and direction, air temperature and humidity, visibility, air pressure and cloud base is also collected. The LMW processes sensor information and upgrades this data to qualified readings. This data is used for multiple purposes at the strategic, tactical and operational levels. For example, hydrological and meteorological data is used at the strategic level to identify long term climate change trends and is used within the Delta Program of the Netherlands to adopt strategies to adapt to and accommodate these climatic changes. The LMW provides a complete technical infrastructure for the gathering and distribution of water data and delivers the data to various stakeholders within and outside RWS such as the Storm Surge Barriers, hydro-meteorological centers, municipal port companies (among others Port of Rotterdam), flood early warning services and other private parties. LMW also produces data about the state of objects such as real-time information about pump rotation times, lift heights, valve positions, operating time and spray times.

### 4.2.2 BOS - Water Authority Delfland

The primary system used by the Water Authority Delfland to manage water levels is BOS (*Beslissing Ondersteunend Systeem*). Water Authority Delfland is a Dutch Water Authority (water board), which is responsible for water management. It covers the municipalities of Delft, Midden-Delfland and The Hague, and is located in the province of South Holland. It is one of the oldest democratically managed public organizations in The Netherlands as it was established in 1289 when William I, Duke of Bavaria authorized the "Heemraden of Delft" to manage water and serve as a separate court. The organization is led by a “Dyke Duke” (Dijkgraaf), who acts as the (non-voting) Chairman of the Board of Governors, which is a general board called "verenigde vergadering", consisting of 30 representatives which are representatives of the inhabitants (21 by direct elections), industry (4), owners of open land (mainly farmers - 4) and owners of natural habitats (1). The Dijkgraaf also heads the general management of the Water Authority as Chairman of the Board of Directors in which he has a more direct management role.

1.4 million people live and work in the area in which Delfland operates, and approximately 40,000 businesses are established in an area of about 41000 hectares. This makes the Delfland region one of the most densely populated and most highly industrialized areas of the

Netherlands. Figure 4-6 below depicts a map of the Delfland management area.

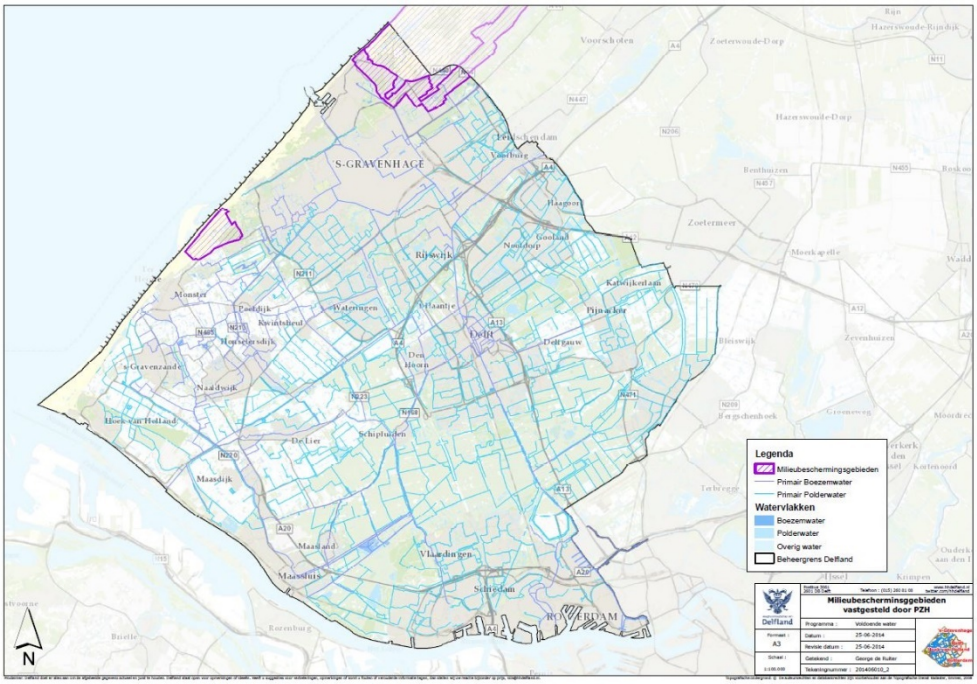


Figure 4-6: Map of the water management area controlled by Water Authority Delfland (Water Authority Delfland, 2014)

The region is also renowned for its intensive glasshouse horticulture. The Delfland region is located below sea level and major flooding would occur if a dune or dyke should give way. The consequences of a collapse in the Delfland region would be felt as far as the Utrechtse Heuvelrug. To limit the danger, Delfland maintains the sea and river flood defense structures. The primary maintenance of dykes and dams in Delfland consists of two components: the seawall and the river flood defense structure. Dykes and dams of Delfland must be able to withstand a wind-force and water level which, on average and statistically speaking, do not occur more than once every 10,000 years.

Traditional water level measurement was performed using a level scale in fresh waterways such as ducts and locks. This was placed during construction of the asset and indicates the depth related to the soil (usually) a plurality of centimeters. The water level is also displayed

relative to the soil, but especially in relation to the Amsterdam Ordnance Datum or "Normaal Amsterdams Peil" (NAP). NAP is a vertical datum in use in large parts of Western Europe. On maps the depth of the soil relative to NAP was usually depicted. With this depth compared to NAP, the water depth was thus be calculated, a time consuming and fault sensitive process.

BOS is the decision support system for the main pumping systems in control of the Delfland Water Authority. BOS has a rich history at Delfland, but received a major upgrade in 2015. The main pumping stations regulate the water levels in the Delfland region. Figure 4-7 below shows the system of polders managed by the Water Authority Delfland.

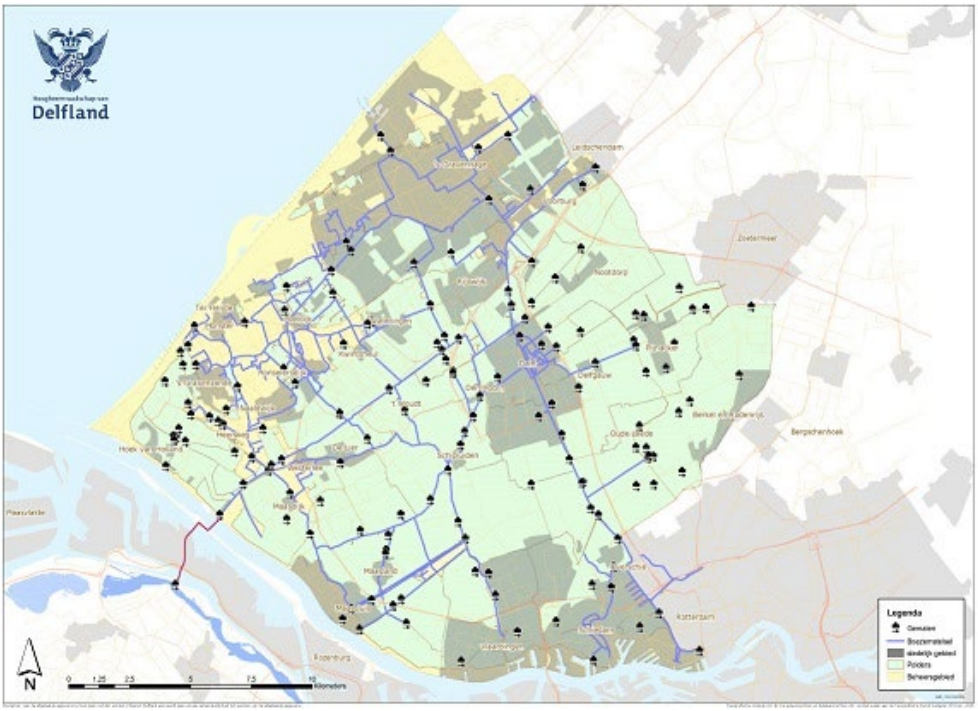


Figure 4-7: Polder system of Water Authority Delfland (Water Authority Delfland, 2015)

Water Authority Delfland manages approximately 3700km of polder ditches, 130 automated polder pumping stations, 20 automated inlets, 100 automated weirs, 100 remote level loggers, 86 smaller pumping stations, 200 smaller pumping stations (not owned by Delfland), circa 3000 fixed weirs and circa 2000 fixed inlets. Figure 4-8 below shows

a photograph of an example of a pumping station, in this case the Harnaskade pumping station in Delft.


Figure 4-8: Harnaskade pumping station, Delft (www.google.com/maps accessed: 2018)

Water management at Water Authority Delfland involves the regulation of the water levels in streams, lakes, ditches, moats and canals. This is vital for industrial development, agricultural businesses, environmental management and recreation. The height at which the water level of an area is set depends on the use and function of that area. For example, although water levels in wildlife areas often fluctuates, farmers tend to prefer a relatively low water level to prevent their land from becoming too wet. Figure 4-9 below shows a screen shot of the BOS user interface.

In the BOS process screen, current measurements are displayed from Delfland telemetry, supplemented by estimations from the BOS. These include inland water levels (upper part of the screen), meteorological information (middle block) and volumetric flow rate (lower part of the screen). BOS Delfland reads precipitation (from rainwater measuring stations) every 15 minutes and water levels on the reservoirs (measured at polder mills). In addition, BOS Delfland receives weather forecasts from MeteoConsult every 15 minutes via FTP. These are 3 files with 1-hour, 3-hour and 24-hour forecasts of precipitation (per hour),

wind (per 3 hours) and evaporation (per day). The relevant level manager indicates which target level should be used (and at what time should be reached) and whether a precipitation protocol is active. BOS Delfland then calculates the desired deployment of each reservoir mill for the next 24 hours and makes a 'request' to the ABB system for use of pumping stations for the current time.


Figure 4-9: User interface BOS (Aankondiging van een opdracht: BOS 2.0 - Hoogheemraadschap van Delfland - Bijlage 7 Functioneel ontwerp BOS 2 0.pdf)

As such, following (Gigli & Koo, 2011), we can classify BOS services as being collaborative aware services, as BOS services are used to make decisions, and based on those decisions, to perform an action. BOS services have “terminal-to-terminal” communication, as a number of pumping mills are automated based on BOS data, as well as “terminal-to-person” communication as BOS data is also distributed to multiple parties.

### 4.2.3 Ground Water Measurement - Municipality of Rotterdam

The third case chosen, at the local level, is that of the automatic measurement of ground water levels in the Municipality of Rotterdam. The water level in the Rotterdam municipality is monitored via sensors placed

in the polders which measure the levels of the groundwater. By combining the data collected by these sensors with data from other sensor systems, for example weather satellites, it is possible to predict whether there is a danger of flooding. Rotterdam is the second-largest city in the Netherlands and one of the largest ports in the world. It is the largest port in Europe and one of the busiest ports in the world. Starting as a dam constructed in 1270 on the Rotte River, Rotterdam has grown into a major international commercial center. It has a strategic location at the Rhine-Meuse-Scheldt delta on the North Sea and is at the heart of a massive rail, road, air and inland waterway distribution system extending throughout Europe. Figure 4-10 below depicts a map of the area controlled by the Municipality of Rotterdam.


Figure 4-10: Map of the Municipality of Rotterdam (www.maps.rotterdam.nl)

The municipality consists of fourteen boroughs which are responsible for many activities that previously had been run by the central city. These have their own council, chosen by a popular election, but they are governed by the central municipal council. Local decisions are made at borough level but affairs pertaining to the whole city, such as major infrastructural projects, are delegated to the central city council. The Municipality of Rotterdam prides itself on a strong economy and an attractive residential environment and profiles itself as a 'water city'. The vision of Rotterdam for the future plays an important role in all of its water

plans for future development. Three crucial developments face Rotterdam municipality in the future. Firstly, higher water levels due to rising sea levels form a risk of flooding in areas outside the protection of the dikes which requires flood defenses to be reinforced. Secondly, flooding caused by increasing rainfall is also expected to form a significant risk in the future. Rotterdam officials expect that climate change will mean increased amounts of rain falling in short spaces of time. In order to process the resulting water, extra provisions will be needed for collection and storage. Rotterdam officials estimate that there is already a shortage of around 600,000 $m^3$ of storage. At least 80 hectares of extra lakes and canals would be needed to be able to cope with this shortage by means of open water. Thirdly, there are stringent demands to be met on water quality (based on the European Framework Directive on Water). Quality profiles, based on these requirements, are in the process of being drawn up for all stretches of water in the city.

Traditional water-level monitoring programs depend on the operation of a network of observation wells—wells selected expressly for the collection of water-level data in one or more specified aquifers. Decisions made about the number and locations of observation wells are crucial to any water-level data collection program. Water-level monitoring programs for complex, multilayer aquifer systems also require measurements in wells completed at multiple depths in different geologic units. Furthermore, traditional monitoring programs also need to find ways to address collection of other types of hydrologic information such as precipitation data. As all traditional measurements are done by hand, the collection of data over long periods of time can be a time consuming and expensive process.

To assist the strategic objectives of the Municipality of Rotterdam, the Rotterdam groundwater measuring system has been recently expanded by more than 300 measuring stations and the total number of measuring stations has reached circa 2000. Figure 4-11 below shows an example of an automatic measuring station. Connecting a measuring tube with sensors to the internet makes it possible to read the water levels remotely. There is a communication via a computer with the test tube, which in Rotterdam often goes through the LoRa network. LoRa is a wireless network which is especially useful for small data streams. Due to the small size of the messages, the battery tends to last longer than other solutions. With this method, water levels can easily be measured and read. The measurement data is available on the Internet.

Information about groundwater levels is the relationship between the actual groundwater status and the reports and complaints about (ground) disturbance and loss of water.

Figure 4-11: Automatic water level measuring station (https://waterwindow.nl/casus/peilbuizen-moeilijk-af-te-lezen)

In any particular area, development or replacement of sewage is generally known to be taken into account, or if the municipality needs groundwater facilities such as drainage, IT sewers, watercourse hardening and wadi's. As such, we can classify the ground water measuring network as being information aggregation services, which refer to the process of acquiring data from various sensors, processing the data, and transmitting and reporting that data via IoT to the application. The sensors in the ground water measuring network work, more or less, one way, as information is collected and sent via the network to applications for processing. Figure 4-12 below shows a screen shot of the digital map with examples of the measuring stations.

Due to a variety of possible causes, such as above average precipitation, soil decomposition, substitution of leaky sewers or excessive surface water levels, groundwater levels may rise at certain locations. The drainage depth then becomes smaller. Groundwater may penetrate into low-lying spaces or cellars, when not waterproof. When working in public spaces, such as road or sewer maintenance, the Municipality of Rotterdam

often increases the ground level to its original level (the so-called issue level). Sometimes this causes flooding in lower lying areas, for example in gardens that are not raised by the owner. Public areas can also be affected by excessive groundwater levels. Examples of these are freezing roads or flooded parks. But the reverse is also possible: if the groundwater level is at a lower level, the drainage depth becomes greater.

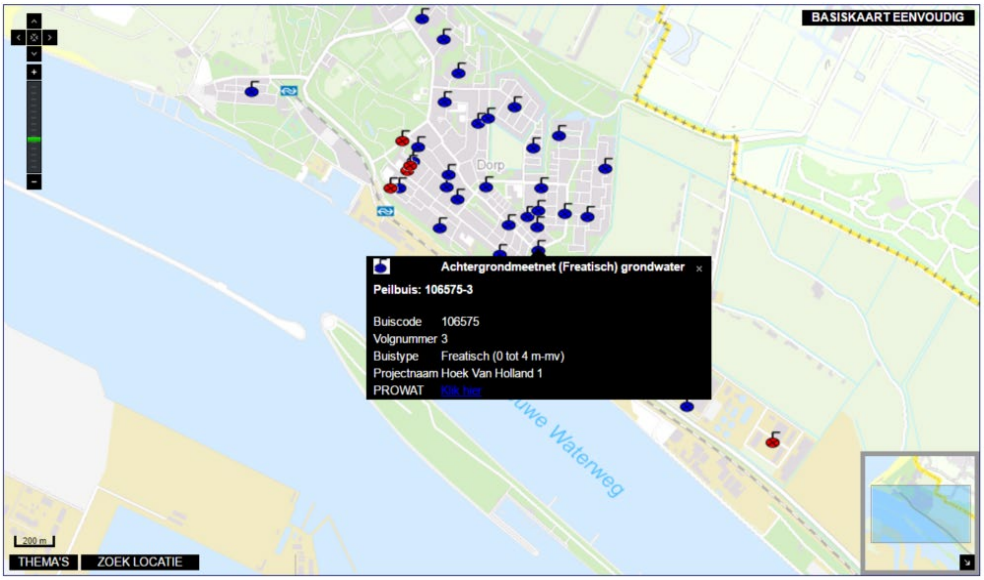


Figure 4-12: Screen shot of the interactive map showing locations of the groundwater measuring stations (http://www.gis.rotterdam.nl/rik/rik.html)

This can be caused, for example, by lowering the surface water level in the area, groundwater extraction or leakage of sewers. Fungi can affect foundation poles of buildings whose foundations are on wooden poles which are partially dry. In case of prolonged dryness, foundations (locally) can collapse, resulting in cracking in the walls. Without intervention, a property will eventually be lost. This information is important for the municipality, but also for citizens and businesses. This is especially true for owners of wooden pole foundation buildings, who want to know if this foundation is dry. As a result, the data is made publicly available digitally on the internet to enable self-service. Sewage systems often reduce the water table in densely populated areas where rainwater is directly piped into the sewage system as opposed to being simply allowed to be absorbed by the soil. Groundwater in Rotterdam is managed by an extensive sewage system. Rotterdam has about 2,400 km

of gravity sewers, 927 septic tanks and pumps, and more than 300 km of vacuum sewers that collect and discharge urban waste water and rainwater to the sewage treatment plants (commonly known as 'RWZI' at Rotterdam Municipality). The nine RWZIs of the water boards handle annually about 80 million $m^3$ of one mixture of urban wastewater, rainwater and groundwater. The RWZIs Dokhaven and Kralingseveer purify the wastewater of the urban area. A centralized system ensures that the effluent water is distributed as evenly as possible between the purification centers. The purified effluent is then discharged into the Maas river.

### 4.2.4 Comparison and Validity of the Exploratory Case Studies

Table 4-4 below shows how the case studies can be compared. The table begins by comparing the case studies to the case study criteria discussed in Chapter 2 to demonstrate the validity of the case studies.

Table 4-4: Summary and Comparison of the Explanatory Case Studies.

| **Criteria** | **Case Studies** | | |
|---|---|---|---|
| 1. The case must occur within a distinct organization. | RWS | Water Authority Delfland | Municipality of Rotterdam |
| 2. The primary processes of the organization must be focused on the management of significant infrastructure. | Surface water management (primary rivers, canals and harbors): system of sensors used to determine variables such as surface water levels which impact the management of infrastructure such as shipping lanes, river bank management, bridges, and storm surge barriers | Surface water management (secondary rivers and canals): water level system used to determine variables such as surface water levels which impact the management of infrastructure such as shipping lanes, river bank management, bridges and polder management | Ground water management: Phreatic measuring system used to determine variables such as surface water levels which impact the management of infrastructure such as sewerage and building foundations |

| **Criteria** | **Case Studies** | | |
|---|---|---|---|
| 3. The case environment should be "data-rich". This means that the organization should produce, manage and maintain at least 5 large datasets as well as a more than twenty small to medium data sets which support the asset management process. | RWS has more than 1000 datasets, including Dutch base registrations such as the Base topography. LMW itself includes water levels, wind speeds, wave height, saltation levels, astronomical tides | Delfland has more than twenty large datasets. BOS itself includes inland water levels, meteorological information and volumetric flow levels | Rotterdam has more than twenty large datasets, including national base registrations such as large scale topography and buildings and addresses. |
| 4. The AMDI must include at least one example of IoT adoption. | LMW<br><br>*Number of stations:* >640<br><br>*Type of services:* Collaborative aware services<br><br>*Age of System:* >20 years (upgrades from 2015 include data transmission upgrades and making data available via webservices)<br><br>*Type of sensors:* Multiple incl. temperature, wind speed etc.<br><br>*Data transmission:* datacom varieties, mostly RJ45 ethernet, over different media, incl. DSL, UMTS, RAM mobile | BOS<br><br>*Number of stations:* >600<br><br>*Type of services:* Collaborative aware services<br><br>*Age of System:* >20 years (upgrades from 2015 include transmission upgrades)<br><br>*Type of sensors:* Precipitation, pressure level sensors<br><br>*Data transmission:* Telemetry, ftp | Ground Water Measurement<br><br>*Number of stations:* >2000<br><br>*Type of services:* Information aggregation services<br><br>*Age of System:* >20 years (upgrades and revisions from 2016 include transmission upgrades and making data publicly available via internet)<br><br>*Type of sensors:* Phreatic pressure sensors<br><br>*Data transmission:* Multiple incl. LiDAR, GPRS, manual data capture |

| **Criteria** | **Case Studies** | | |
|---|---|---|---|
| 5. The case should occur within The Netherlands. | Case encompasses the primary rivers and canals of the Netherlands and is managed by Dutch central government | Case encompasses the secondary rivers and canals of a specific region of the Netherlands and is managed by Dutch regional government | Case encompasses the ground water levels and sewerage network of a municipality in South Holland, a province of the Netherlands |
| 6. The organization should be of type government or semi-government (majority shareholders should be government). | *Type*:<br>Central Government<br><br>*Stakeholders*:<br>Asset Managers, General public, Shipping and Transport industry, Logistics, Harbor Management, Meteorology, Regional and local water management, International water management | *Type*:<br>Regional Government<br><br>*Stakeholders*:<br>Asset Managers, General public, Private asset owners, Industry, Agriculture, Municipalities, Other Water Authorities | *Type*:<br>Local Government<br><br>*Stakeholders*:<br>Asset Managers, General public, Water Authorities, Industry |
| 7. Cases should occur at varying geographic coverage levels. | National | Regional | Local |
| 8. Cases should occur in varying asset management domains. | Surface water management: primary rivers and canals | Surface water management: secondary rivers and canals | Ground water management |
| 9. The organization must be willing to cooperate with researchers and must be willing to provide access to the information required for the research. | RWS provided full access to the researchers – see table 2-4 | Delfland provided full access to the researchers– see table 2-5 | Rotterdam provided full access to the researchers– see table 2-6 |

Table 4-4 above demonstrates that the case studies comply with the criteria as specified in Chapter 2. Furthermore, the data was collected according to the case study protocol and was stored in the case study database as per the suggestions made by Yin (2009) which established a

chain of evidence. The data included multiple sources of evidence and key informants reviewed the draft case study report. As such we may conclude that the results of the case studies as summarized in the sections below are reliable and valid.

### 4.2.5 Summary of IoT Usage

Table 4-5 below summarizes how IoT is used in the exploratory case studies and how IoT adoption has impacted the asset management process, and answers Research Question 1a. Table 4-2 also derives requirements for the design of the AMDI model.

Table 4-5: Comparison of how IoT is used in the cases and the effect of IoT on the AM process –answer to Research Question 1a.

| **Attributes** | **Case Studies** | | |
|---|---|---|---|
| ***IoT system name*** | **LMW** | **BOS** | **Ground Water Measurement** |
| ***Organization Name*** | **RWS** | **Water Authority Delfland** | **Municipality of Rotterdam** |
| *Technical differences:* IoT adoption changes performance measurement of infrastructure service<br><br>*Derived Requirements:*<br>- The AMDI model should provide a method to document the IoT system for future reference<br>- The AMDI model should be loosely coupled, following the principles of linked open data | Adoption of IoT has introduced more detailed and accurate predictive analysis for management of water levels and water quality of major waterways in The Netherlands. LMW collects, aggregates and models data to accurately predict water levels and water quality. Based on these models, decisions are made to close storm surge barriers, close swimming areas, send out messages to shipping etc. | Adoption of IoT has introduced more detailed and accurate predictive analysis for management of water levels in regional waterways. BOS calculates the desired deployment of each reservoir mill for the next 24 hours and schedules use of pumping stations for the current time. | Adoption of IoT has introduced more detailed and accurate predictive analysis for management of ground water levels for the functioning of municipal sewerage systems. IoT has improved the effective collection, transport and processing of rainwater by updating current precipitation information combined with the ground water measuring network in a framework for balancing the collection and transport of rainwater and domestic wastewater, which allows the municipality to anticipate and |

| **Attributes** | **Case Studies** | | |
|---|---|---|---|
| ***IoT system name*** | **LMW** | **BOS** | **Ground Water Measurement** |
| | | | prepare for the collection and disposal of large amounts of rainwater. |
| *People Differences:* IoT adoption changes perception of infrastructure service<br><br>*Derived Requirements:*<br>- The AMDI model should be easily shared<br>- The AMDI model should provide a point of reference for designers to extract system specifications for IoT adoption in asset management organizations | Adoption of IoT has allowed greater transparency of conditions in the Dutch waterways and an increased trust in the substantiation of decision-making, as reported by the interviewees. The functional requirements of the LMW are based on the information needs of the RWS primary process. However, the data is also used by other users such as:<br>-Professional users like other government agencies, engineering agencies, universities and professional services<br>-The general public such as sailors, surfers, etc. | Adoption of IoT has allowed greater transparency of conditions in the Delfland waterways and an increased trust in the substantiation of decision-making as reported by the interviewees. The height at which the water level of an area is set depends on the use and function of that area. For example, although water levels in wildlife areas often fluctuates, farmers tend to prefer a relatively low water level to prevent their land from becoming too wet. BOS allows Delfland to accurately communicate reasons for decisions regarding water levels. | Adoption of IoT has allowed greater transparency of conditions in the municipal sewerage systems as, for example, when working in public spaces, such as road or sewer maintenance, the Municipality of Rotterdam often increases the ground level to its original level. Sometimes this causes flooding in lower lying areas, for example in gardens that are not raised by the owner. As such, IoT allows the Municipality to accurately communicate reasons for decisions regarding water levels. |
| *Organizational differences:* IoT adoption changes improvement processes of infrastructure service<br><br>*Derived Requirements:*<br><br>- The AMDI model should adhere to | IoT adoption has allowed asset managers access to greater levels of up-to-data information regarding the state of the Dutch National waterways and has greatly increased efficiency in the collection of this | IoT adoption has allowed asset managers access to greater levels of up-to-data information regarding the state of the regional waterways and has greatly increased efficiency in the collection of this data, making the | IoT adoption has allowed asset managers access to greater levels of up-to-data information regarding the state of the municipal sewerage systems and has greatly increased efficiency in the collection of this data, making the decision-making |

| Attributes | Case Studies | | |
|---|---|---|---|
| ***IoT system name*** | **LMW** | **BOS** | **Ground Water Measurement** |
| conceptual modelling best practices<br>- The AMDI model should be interoperable | data, making the decision-making less subjective. For example, the information about the state of objects from the LMW contains real-time information about pump rotation times, lift heights, valve positions, operating time and spray times. | decision-making less subjective. For example, this means greater insight into which preventive measures should be taken regarding water pollution if severe rainfall is expected. | less subjective. For example, insight can be gained on how salt intrusion occurs in regional waters. This insight can be compared at a later stage with data on soil erosion, and can improve insight into the correct salt-limiting measures. |

The following section describes the first view of the explanatory case studies and discusses potential benefits and risks of IoT adoption in asset management in answer to Research Questions 1b and 1c.

## 4.3 View 1: Practice Perspective

The structure of the exploratory case study descriptions in section 4.3 is as follows:

- Benefits and risks of IoT as a product of human agency
- Benefits and risks of IoT as a medium of human agency
- Benefits and risks of organizational conditions of interaction with IoT
- Benefits and risks of organizational consequences of interaction with IoT

The various structures of each of the views are presented in the introduction of each section. The cases are described in the following order: National (RWS), Regional (Water Authority Delfland), and, finally, Local (Municipality of Rotterdam). At the end of the section, a comparison of the cases is provided.

### 4.3.1 LMW – Rijkswaterstaat

LWM has greatly improved the efficiency, effectiveness and flexibility of a wide variety of public services, as the gathering of this data is centralized and each service no longer has to gather the data themselves. However, in order to be useful, the data needs to be measured in a standardized

way. But conditions at the different measuring stations can be location specific. Therefore, to reduce complexity, RWS has had to standardize the method of converting raw sensor signals to metrics, including validations and conversion calculations. This is an internal RWS standard. LMW has also faced serious IT infrastructural limitations as there are various aspects that determine the limit of the life span of a measuring station such as availability of components, a dependable producer of components, the number of suppliers with similar components, life expectancy of the components, and maintainability of the software etc. These are areas where RWS sees opportunities for consolidation.

Automating data collection has produced large quantities of high quality data which allows RWS and other parties to identify trends over time. However, data quality issues have also been experienced. For example, salt content is not measured directly but calculated from the measured electrical conductivity (Ge) and the temperature (Tw) of the water. The current and stored salt content data is used by various agencies. For example, by the Hydro Metric Center (HMC) and Applied Research Water (TOW) for monitoring and controlling the salt / freshwater aquaculture. Ship owners use salt data for determining load capacity and depth of ships, lockers and bridge guards, and the data is also used by drink water companies, and by water boards for agriculture, etc. In addition, the measured data is stored in DONAR (Data Storage, Water, Rijkswaterstaat) after validation. DONAR is a large (archived) database for the storage of water data. The electrical conductivity and the temperature of the water are measured with sensors (inductive measuring cell type FSI CTS-C1DH CT). The challenge here is that measurements of sensors can be polluted (due to algae growth, etc.) so that the signal weakens and reduces the quality of the measurement. To ensure reliable measurements these sensors need to be regularly checked and cleaned. Pollution of the measurement is (amongst other things) dependent on the temperature, light (the season), and the type of water (salt or fresh). The duality here is that regular maintenance of the sensor network needs to be carried out, work which previously did not exist, and which adds to the total cost of ownership of the data. Furthermore, the risk exists that incorrect data due to quality issues such as those detailed above corrupt the system leading to incorrect actions being taken based on incorrect values.

The centralized gathering of data has greatly reduced the overall cost of data collection as a whole, as the data is collected only once by one source and shared between partners. The sharing of data as “open data” has introduced new revenue streams as businesses are able to

provide new services using data created by the LMW network, such as developing new models which are used in planning and maintenance or to provide services for the maintenance and management of the LMW sensors. The duality is that it falls to RWS to bear the total cost of ownership of the system, as the data is provided free of charge to all other parties as "open data". According to an RWS official, "because of the number of measuring stations and the geographic spread of the sensors, implementation and maintenance of the sensor network is a costly affair". LMW enables timely data with regards to the situation in rivers, canals and sea via sensors at approximately 640 monitoring sites. Monitoring sites are managed and administrated partly by RWS (approximately 300 physical measurement locations) but also partly by external parties (approximately 340 monitoring stations). This means that RWS has to maintain departments to perform management and maintenance tasks, as well as departments to manage the external parties tasked with maintenance of the monitoring stations. The duality is that the system has had an integral effect on the organizational structure of RWS, as RWS was forced to adopt a splintered approach to maintenance and management of the entire system, by outsourcing the maintenance of parts of the system and managing parts of the system themselves. This is due to a perceived lack of technical knowledge in the market and the wide variety of different types of equipment with different coupling technologies used by the measuring stations. Furthermore, because of the complexity of the system, there are a number of interoperability issues and there is a serious lack of knowledge which has forced RWS to continue to maintain the system itself. There are at least 30 different types of sensors used in the network. There are also several different types of external links to other organizations for the exchange of data.

Water levels in shipping are closely monitored to ensure that ships of a certain class are able to traverse the shipping lanes. At periods of low water levels, for example, certain classes of ship have too deep a keel and would get stuck on the bottom. Also, if the water levels are too high, some classes of ships would not be able to pass under bridges. It has happened that ship captains misjudge the clearance of the bridge and collide with the bridge causing major structural damage. LMW provides detailed, up to date data to help prevent this from happening. Clearances are able to be judged more finely and regulations can be made more efficient and can be more efficiently enforced. The duality is that LMW has changed how shipping is managed. RWS now has more control over the water levels in the water system and can communicate these levels to captains who are able to time their trips more finely. Captains are always ultimately

responsible for accidents involving bridges which are too low, but the duality is that reliance on IoT data for planning purposes may lead to reduced levels of concentration for location specific issues. This case shows that legal frameworks may need to be further developed where discrepancies arise between communicated water levels based on IoT data and actual local water levels.

This distribution of data greatly improves the transparency of the decisions and advice given by RWS such as when to close the storm surge barriers or when certain waterbodies are restricted to public access. Citizens have been empowered to decide where and when they wish to swim in open water, as the water quality of open water bodies is now publicized. Figure 4-13 below shows a screen shot of the swimming water quality app, developed to empower citizens.

LMW has greatly contributed to the advanced forecasting of water levels and the monitoring of trends. But, LMW also includes data from third parties, including water data from foreign countries and other public organizations within The Netherlands. RWS is restricted from sharing externally created LMW data with other third parties due to requirements imposed on them by the participating parties. The LMW measures a wide variety of hydrological data such as water levels, flow rates, wave heights and directions, flow velocity and direction, and water temperature. LMW is a mission-critical network which is vital to the national security of The Netherlands. This requires continuous and distributed monitoring and management. The duality is that security is of vital importance to the LMW system, and RWS has had to ensure that redundancy is built into the system wherever possible to ensure continuance of service.

Storm surge barriers are movable dams in estuaries and waterways. They protect sensitive areas from flooding. Storm surge barriers are often used to protect harbors, and these need to be closed in times of high water. The LMW makes it possible to automate this process based on accepted norms and using well tested models, greatly reducing the time required to act in emergency situations. The risk is that if LMW distributes incorrect data due to either mechanical or human defects, the system may erroneously indicate that the storm surge barriers should close when this is not necessary, or worse, that the surge barriers should not close when it is necessary. Closing a storm surge barrier unnecessarily can have enormous economic impact as shipping is unable to offload goods according to schedule.

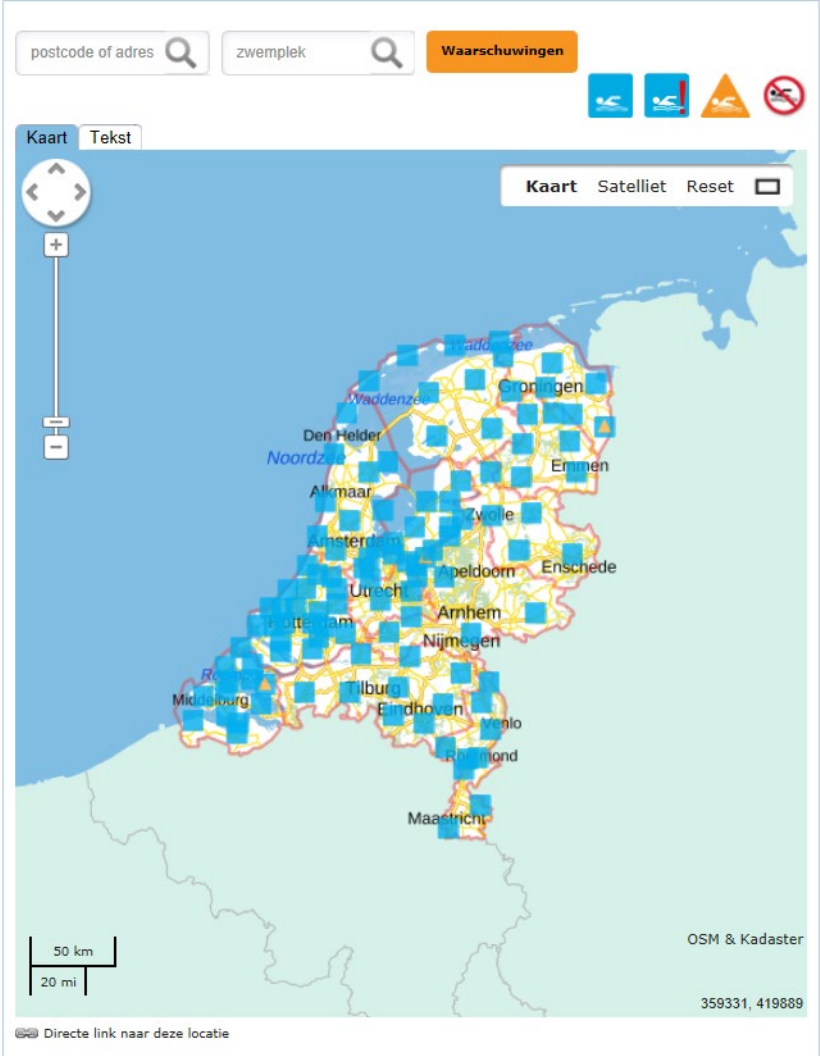


Figure 4-13: Screen shot of the swimming water quality app (http://www.zwemwater.nl/home)

If a storm surge barrier does not close when necessary, the consequence for The Netherlands may be a national disaster due to (potential) widespread flooding. As such, if water levels reach 3 meters above Amsterdam ordnance zero, and there is no further intervention, the arms of the "Maeslantkering" (Maeslant storm surge barrier) are activated automatically. Under normal circumstances, these doors are fully opened, so that the ships have access to the port of Rotterdam. The intention is

that the barrier should only be closed under exceptional circumstances - no more than once or twice every ten years. The doors are stored in docks, which lie along both shores.

### 4.3.2 BOS – Water Authority Delfland

The Water Authority Delfland is known as a water board that attaches great importance to innovations. In this context, Delfland sees opportunities to support and optimize its primary processes by using smart IT. Within the water board, a lot of information is gathered on site ("in the field"), for example by inspectors, subcontractors, and so forth. The handling of such work is traditionally done through an administrative process and partly by hand. The introduction of modern devices like smartphones and tablets, has meant that this process is performed faster and more efficiently. In concrete terms, this means greater insight into the locations where rainwater storages are located in the Westland area and what its effect on water management is. On a more operational level, if severe rainfall is expected, water pollution can be limited by taking preventive measures, such as premature spraying and premature discharge of existing basins, then storing excess rainwater in these existing basins. Water Authority Delfland’s ambition is to get more information from the already known source data by combining it with other available data sources such as IoT data, GIS data and weather forecasts or tidal information. Water Authority Delfland has IoT data sources for water levels, and a separate database for water quality. A separate database is also maintained for the management of assets. These databases are semantically linked.

Delfland employees 'in the field' often arrive at unexpected situations on a daily basis, such as faulty equipment, broken installations, cracks in dykes, and so forth. But it still often takes a lot of effort to get access to the right asset information to able to make judgments on the correct course of action. In addition, they have to provide through a fairly cumbersome (paper) administrative procedure for repairs. Rapid access to data sources in the field can make this process more efficient. But, actions taken based on incorrect data may be counterproductive and expensive, creating problems for the organization as a whole. Officials at the Water Authority Delfland have quoted this risk as being the reason why they spend a good deal of time on ensuring that they have a good overview of their data landscape. This is important in case of calamities. For example, one official at Water Authority Delfland gave an example of an instance when a particular water way emptied at rate which astonished everyone at the time. When looking at the data, the reason was not

immediately obvious, but it eventually became clear that there was an open culvert which they did not know existed which was causing the drainage. If the asset managers had known that the culvert was there they would have thought of this first, but trusting the data in this case led them away from the solution.

To prevent similar cases happening regularly, Water Authority Delfland has an extensive data management process operating within the organization. Water Authority Delfland focusses on ensuring data quality during data creation. Data that is generated automatically through IoT is considered of high quality. However, this data often needs to be linked with other, static data in order to be able to gain the potential benefits. Water Authority Delfland believes that it is necessary to make demands on the quality of the data. Officials believe that there are differing levels of maturity regarding data quality management. An official quoted data quality issues as having negative effects on the budgets of asset managers which led to increased levels of effort. This shows duality as data quality led to additional roles being defined within the organization to manage the data. Water Authority Delfland has an administrative team to ensure that the data is in order, and there is political pressure to deliver results. The political head of the Water Authority, the "Dyke Duke" is quoted by officials as being in favor of a number of drivers including data management and that they have therefore embraced an extended work plan, including introducing the role of data owner. As such, a great deal of time has been spent on managing teams. Also a great deal of consultation work has been carried out with a particular look at improving cooperation, the example quoted was that of Ijkdijk. The duality is that Water Authority Delfland still needs people to validate the data, despite the automation of the data collection through the application of sensors. In the field, especially in a densely populated area, the asset infrastructure is changing constantly, as assets are replaced and renewed and these changes need to be reflected and validated in the system to ensure that the system reflects the situation on the ground. At Water Authority Delfland, this work has been organized in teams, with the idea being that teams share responsibility for the data. This team forming (to ensure data quality) has had a significant impact on the organizational structure due to reorganization, as well as the organizational culture as teams become more data oriented.

The penetration of salt through the Park Locks in Rotterdam on the river Schie is a known phenomenon. The main water system (the Nieuwe Waterweg) and the Schie (Water Authority Delfland area) merge at the

Park Locks. Figure 4-14 below depicts an overview of the Parks Locks as seen from the Euromast in Rotterdam.

Figure 4-14: Overview of the Parks Locks Seen from the Euromast (Rijksdienst voor het Cultureel Erfgoed, 2015)

By establishing a new regional measurement network and by combining (data) in a customized model, insight can be gained on how the salt intrusion occurs in regional waters. This insight can be compared at a later stage with data on soil erosion, and can also be based on salt-limiting measures (rinsing, regulation of sluice times, etc.). This case shows that adoption of IoT has duality as asset management processes need to be restructured based on new insights. As such, Water Authority Delfland are also exploring how intelligent handling of information, such as how much storage capacity is available in shelter reservoirs, can be anticipated, and how to deal with water pollution in a particular area as soon as possible. Becoming more data driven has led to deepened awareness within Delfland how important it is to connect information and data from different data sources. Previously this was limited and only possible with great effort. A technical solution has been sought for these issues due to the need to connect different databases and systems. Delfland can now access, and make available, various data to and from their own technical environment. The duality is that implementing this ESB and various related projects has also led to more integrated

cooperation between the various departments of the Water Authority Delfland.

However, some officials interviewed also suggested that Water Authority Delfland may still be distracted from data collection via the Open Data principle. In addition to the suspicion that others may use data for "reasons other than intended", there is still insufficient assurance as to the liability of organization that generates data and provides it to a user. As such, this case shows the duality that Water Authority Delfland has been structured by technology by developing and implementing a standard disclaimer when making their own data available to third parties. Officials believe that the reason for not making data available is “because of the loss of control over where the data is used or how”. This fear decreases as it is known that the situation already exists in some form such as with the Dutch National Base Registrations and the knowledge that data from third parties may add value. The belief holds that data sharing is only useful if users know what data is available and how the data adds value to primary processes.

At Water Authority Delfland, asset management focuses on ensuring acceptable risk at a coordinated level. But the feeling expressed by some of the interviewees is that “a good deal of knowledge still resides in the heads of experts”. The risk being that as the organization ages, it becomes harder to quantify this expert knowledge or make it explicit, and the organization becomes difficult to manage. Some of the interviewees believed that “when asset management is carried out by individuals in this way, an attempt is always made to ensure perfection as professionals, by nature, take pride in their work”. However, perfection is costly and often not always necessary. By becoming more data driven, Water Authority Delfland believes that asset management can be approached in a more centralized manner in which the risk of failure can be weighed up in a more objective manner at a higher system level. The example given was that when dredging or planting activities are required, it is also necessary to take into account risks of going over budget. The duality is that it is necessary to put a more structured maintenance regime into place, but this is only possible with high quality data and central information control. This case shows that adoption of IoT structures organizations by moving the span of control over assets from individual asset managers with high levels of local knowledge, to a more centralized, system-based way of working.

### 4.3.3 Ground Water Measurement – Municipality of Rotterdam

The municipal sewerage plan sets out the approach for the most urgent foundation risk areas (areas with wooden pole foundations, which pose a risk of wood rot due to dryness). The ambition in 2016 was to replace eighty km of leaking sewage before 2021 in these areas. However, it was assessed that this ambition was insufficiently substantiated. It was decided that the approach in these areas required more research into the relationships between sewerage, groundwater and foundation damage. Figure 4-15 below shows a screen shot of the "Foundation Window", an application which shows the risk level of areas in Rotterdam.

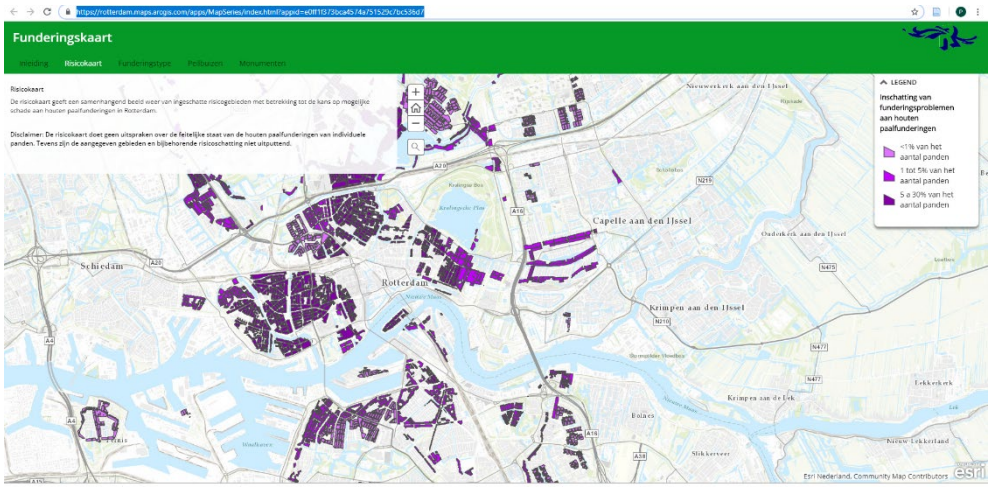


Figure 4-15: A screen shot of the "Funderingsloket" – an application showing the risk levels of wood rot in Rotterdam (https://rotterdam.maps.arcgis.com/apps/MapSeries/index.html?appid=e0ff1f373bca4574a751529c7bc536d7)

In 2014, the Groundwater Quantity Bill (2011) was evaluated by Rotterdam Municipality based on a number of cases (Municipal Sewerage Plan 3, 2015). The evaluation showed that the criteria with which structural groundwater underload is objectively decided is not yet entirely established. The suggestion is that the current criteria for structural groundwater pollution cannot be applied in setting-sensitive areas due to environmental impacts of, for example, undeveloped buildings. It was therefore difficult to determine objectively whether a measure is effective. As such, the ground water measuring network has been greatly extended

by more than 300 measuring tubes to circa 2000, the data of which is available on the internet. It is important to note that Rotterdam municipality only manages sensors which have been placed on public land. The purpose of expanding this network was to ensure that groundwater issues do not become a structural barrier to land use. The data provided by the ground water measuring network shows a distinct correlation between actual ground water status and the number of reports and complaints regarding issues due to surface water fluctuations. The duality is that Rotterdam Municipality now works far more proactively by taking these issues into account in areas of development or replacement of sewage, instead of reactively waiting for complaints. Rotterdam Municipality is now also able to communicate more efficiently with the public, as well as being able to introduce extra facilities such as extra drainage, watercourse hardening and wadi's before disruptions and public inconveniences occur. As such the ground water network contributes extensively to improving the public perception of Rotterdam.

Rotterdam has implemented asset management in the municipal organization, and because the budgets are limited, more substantiated accountability is required and the role of the Government changes. The goal being "to make budgets even more effective and to manage assets more efficiently". The latest techniques and models, driven partly by data from the ground water network, are used for this. In the words of Rotterdam officials, "it is no longer the accepted norm, but the balance of risk and cost that determines the decision to repair or replace an asset". This ensures clarity as to the considerations are for a decision. In this plan, Rotterdam further fulfills its role as a supporting governing body, ensuring empowerment of citizens by encouraging private parties to be self-reliant and to take responsibility for mitigation measures in the (waste) water chain, such as in the field of drainage and groundwater measurement. Rotterdam officials believe that governments are becoming increasingly believable, but this believability "is reliant on releasing information based on quality data". Guaranteeing quality of data within the Rotterdam data infrastructure is seen by officials as being highly complex and reliant on high levels of "missionary work" to ensure that awareness of data quality remains high. At the time of writing, it was reported that "no structural insight into the quality of the data was being made". It was felt that at the operational level, people know the quality and take action where necessary, but if when people doubt the quality of the data, they keep their own registrations, without legacy metadata. It was reported that plans were being made to address his in a structural way.

Using IoT data to drive decision making, the Rotterdam Municipal Sewerage Plan attempts to achieve a number of goals. A primary goal is urban waste water collection and transportation. Virtually all properties on the municipal area of Rotterdam, including the Greenhouses, have municipal sewerage or have an individual wastewater treatment system (IBA). Owners of houseboats are motivated to connect their houseboats to the sewerage system and obtain advice from the municipality. According to Rotterdam officials, the planned replacement of free trap drainage has also been achieved, using indicators like age, type of system, settlements and hydraulic function etc. The duality shown is that management and maintenance of the sewerage network is becoming increasingly regional or district-oriented. This territorial approach, also shows a gradual process of alignment with external parties.

Another primary objective of the municipal sewerage plan is the effective collection, transport and processing of rainwater. The rain radar (2015) on the building "Delftse Poort" updates current precipitation information, and, combined with the ground water measuring network (amongst other sources) in a framework for balancing the collection and transport of rainwater and domestic wastewater, allows the municipality to anticipate and prepare for the collection and disposal of large amounts of rainwater. This case demonstrates duality as one of the applications is the "green roofs" stimulus program. Figure 4-16 below depicts an example of a "green roof" in Rotterdam. The application of IoT data has stimulated about 140,000 $m^2$ of green rooves over the last 5 years. As such, IoT data is beginning to structure how Rotterdam develops as a city. Furthermore, insight into the hydraulic functioning of the system allows Rotterdam municipality to ensure prevention of disruptions due to water fluctuations and to ensure security from flooding. Insights provided by the data has meant that the sewage system can process the fallen precipitation according to the design standards without disruptions due to unwanted surface water. Evaluations of extreme precipitation events demonstrate the robustness of the system which contributes to a positive public perception. IoT adoption has allowed Rotterdam to actively communicate with citizens and companies. Active communication means that citizens become more empowered by becoming more aware and being more involved in planning activities. For example, citizens are being motivated to catch rainwater from their rooves.

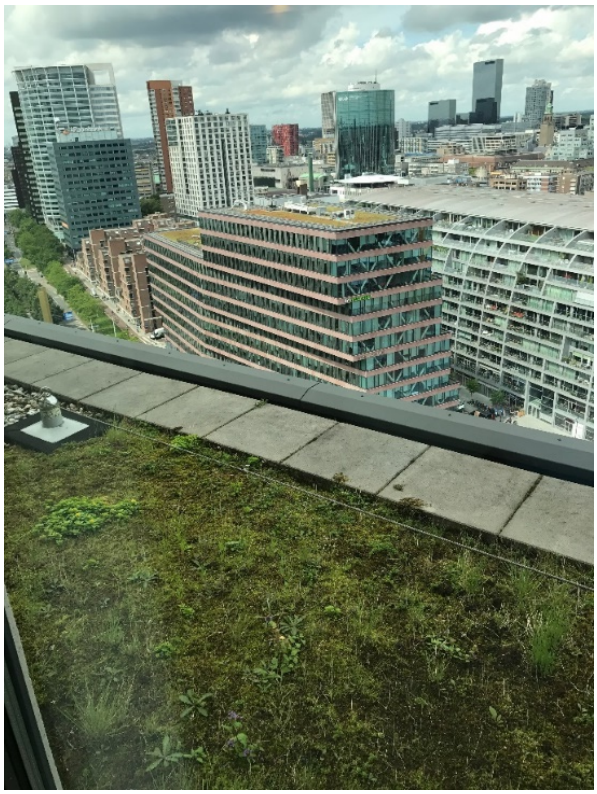

Figure 4-16: “Green Rooves” in Rotterdam

Attention is paid to making the responsibilities of the citizen explicit. For example, citizens receive information based on IoT data about the flood risks and the measures that they can take in such a situation. This case shows duality as IoT data drives the policy behind the action "tiles out, green in”, which encourages citizens to grow their own gardens instead of using tiles, and the action against grease and wipes in the sewer. IoT adoption drives the provision of information, as well as promoting self-reliance and self-responsibility of residents, education, innovation and sustainability.

### 4.3.4 Summary of View 1

Table 4-6 below summarizes the benefits of IoT adoption in asset management as identified in the three exploratory case studies. In this section we compare the exploratory case studies and answer Research Question 1b and 1c.

Table 4-6: Benefits of IoT and answer to Research Question 1b.

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| *Technology changes: benefits of IoT as a product of human agency* | Adoption of IoT has improved flexibility, effectiveness and efficiency of services as asset managers are now able to respond to changing conditions at near real-time speeds. For example, instead of having to wait for weather reports and decide on actions subjectively, asset managers are now able to automate processes such as closing storm surge barriers based on analysis of real-time data and accurate predictive analysis. | Adoption of IoT has improved flexibility, effectiveness and efficiency of services as asset managers are now able to respond timely to changing conditions. For example, water management of local reservoirs and polders can be largely automated based on combinations of real-time and near real-time data. | Adoption of IoT has improved flexibility, effectiveness and efficiency of services as asset managers now have up-to-date information available with regards to the functioning and capacity of the sewerage systems and are able to timely redirect flow based on up-to-date local ground water levels. |
| *People changes: benefits of IoT as a medium of human agency* | Adoption of IoT has improved transparency of decision-making and citizen empowerment by publicizing protocols and clarifying when and how actions are taken. For example, citizens and transport companies are now kept up to speed as to when flooding may occur and when storm surge barriers may be closed or polder reservoirs intentionally flooded. | Adoption of IoT has improved transparency of decision-making and citizen empowerment by publicizing protocols and clarifying when and how actions are taken. For example, Delfland works closely with garden farmers and local citizens to maintain local water levels and stakeholders are continually informed when and how actions are and should be taken. | Adoption of IoT has improved transparency of decision-making and citizen empowerment by publicizing protocols and clarifying when and how actions are taken. For example, when the municipality intentionally raises ground water levels, citizens and industry are now informed in a timely manner so that appropriate action may be taken. |

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| *Organizational changes: Benefits related to organizational conditions of interaction with IoT* | IoT adoption has forced the introduction of tightened regulations and has greatly assisted the enforcement of said regulations. For example, water quality can be locally controlled and when norms are broken, the enforcement of environmental regulations can be more easily localized and enforced. | IoT adoption has forced the introduction of tightened regulations and has greatly assisted the enforcement of said regulations. For example, garden farmers and local citizens can now be held to greater responsibility with regards to local water management, freeing up the Water Authority to concentrate on the bigger picture. | IoT adoption has forced the introduction of tightened regulations and has greatly assisted the enforcement of said regulations. For example, whilst citizens are being motivated to catch rainwater from their rooves, attention is paid to making the responsibilities of the citizen explicit. For example, citizens receive information based on IoT data about the flood risks and the measures that they can take in such a situation. |

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| *Organizational changes: benefits related to organizational consequences of interaction with IoT* | IoT adoption has benefitted the organization by improving planning and preventing unnecessary spending, thus reducing cost, through greatly improved trend analysis and forecasting. For example, investment in new assets can now be made on greatly refined data which allows greater refinement to future flooding models due to rising sea levels, greater precipitation etc. | IoT adoption has benefitted the organization by improving planning and preventing unnecessary spending, thus reducing cost, through greatly improved trend analysis and forecasting. For example, insight has been gained on how salt intrusion occurs in regional waters. This insight is compared with data on soil erosion, and now directs salt-limiting measures such as rinsing, regulation of sluice times, etc. | IoT adoption has benefitted the organization by improving planning and preventing unnecessary spending, thus reducing cost, through greatly improved trend analysis and forecasting. For example, insight into the hydraulic functioning of the system allows Rotterdam municipality to ensure prevention of disruptions due to water fluctuations and to ensure security from flooding. Insights provided by the data has meant that the sewage system can process the fallen precipitation according to the design standards. |

Table 4-7 below summarizes the risks of IoT adoption in asset management as identified in the three exploratory case studies.

Table 4-7: Risks of IoT and answer to Research Question 1c.

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| *Technology changes: Risks of IoT as a product of human agency* | IoT adoption presents a risk to AM as difficult interoperability and integration and IT infrastructural limitations can cause data quality issues which may affect the quality of predictive analysis. For example, measurements of sensors can be polluted (due to algae growth, etc.) so that the signal weakens and reduces the quality of the measurement. To ensure reliable measurements these sensors need to be regularly checked and cleaned. | IoT adoption presents a risk to AM as difficult interoperability and integration and IT infrastructural limitations can cause data quality issues which may affect the quality of predictive analysis. For example, IoT data often needs to be linked with other, static data in order to be able to gain the potential insights, but there are differing levels of maturity regarding data quality management at Delfland, and differing levels of data quality which reduces the reliability of the insights. | IoT adoption presents a risk to AM as difficult interoperability and integration and IT infrastructural limitations can cause data quality issues which may affect the quality of predictive analysis. For example, No structural insight into the quality of the data is being made. People have an idea of the quality and take action where necessary, but when people doubt the quality of the data, they keep their own registrations, without legacy metadata. |
| *People changes: Risks of IoT as a medium of human agency* | IoT adoption presents a risk to AM as issues such as data quality can cause a lack of trust and a lack of acceptance of the results of IoT. For example, if LMW distributes incorrect data, the system may erroneously indicate that the storm surge barriers should close when this is not necessary, or worse, that the surge barriers should not close when it is necessary. | IoT adoption presents a risk to AM as issues such as lack of sufficient knowledge can cause a lack of trust and a lack of acceptance of the results of IoT. For example, it is difficult to determine objectively whether a measure is effective as the criteria with which structural groundwater underload is objectively decided is not yet entirely established. The suggestion is that the | IoT adoption presents a risk to AM as issues such as data quality can cause a lack of trust and a lack of acceptance of the results of IoT. For example, citizen trust in local government is reliant on releasing information based on quality data, but guaranteeing quality of data within the Rotterdam data infrastructure is seen by officials as being highly |

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| | Closing a storm surge barrier unnecessarily can have enormous economic impact as shipping is unable to offload goods according to schedule which would severely impact the trust that people place in the system. | current criteria for structural groundwater pollution cannot be applied in setting-sensitive areas due to environmental impacts of, for example, undeveloped buildings. | complex and reliant on high levels of "missionary work" to ensure that awareness of data quality remains high. |
| *Organizational changes: Risks related to organizational conditions of interaction with IoT* | IoT adoption presents a risk to AM as issues such as a lack of clarity with regards to decision-making frameworks can create uncertainty as to what data may or may not be used and what the organizational consequences are for non-compliancy. For example, RWS maintains an open data policy, but is restricted from sharing externally created LMW data with other third parties due to requirements imposed on them by the participating parties. This creates tension as it is not always clear which data falls under the open data policy and which not. | IoT adoption presents a risk to AM as issues such as a lack of clarity with regards to decision-making frameworks can create uncertainty as to what data may or may not be used and what the organizational consequences are for non-compliancy. For example, Delfland may still be distracted from data collection via the Open Data principle due to the suspicion that others may use data for purposes for which it is not meant. There is still insufficient assurance as to the liability of Delfland with regards to data use by third parties. | IoT adoption presents a risk to AM as issues such as a lack of clarity with regards to decision-making frameworks can create uncertainty as to what data may or may not be used and what the organizational consequences are for non-compliancy. For example, it is difficult to determine objectively whether a measure is effective as the current criteria for structural groundwater pollution cannot be applied in setting-sensitive areas due to environmental impacts of, for example, undeveloped buildings. |

| Concept | Case Studies | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| *Organizational changes: Risks related to organizational consequences of interaction with IoT* | IoT adoption presents a risk to AM as issues such as high implementation costs can be a deterrent for innovation. For example, it falls to RWS to bear the total cost of ownership of the LMW system, although the data is provided free of charge to all other parties as "open data". Because of the number of measuring stations and the geographic spread of the sensors, implementation and maintenance of the sensor network is a costly affair. | IoT adoption presents a risk to AM as issues such as high implementation costs can be a deterrent for innovation. For example, rapid access to data sources from the field and data from the outside location can make the AM process more efficient at Delfland, but actions taken based on incorrect data may be counterproductive and expensive, creating problems for the organization as a whole. | IoT adoption presents a risk to AM as issues such as high implementation costs can be a deterrent for innovation. For example, as municipal budgets are limited, more substantiated accountability is required and the role of the Government changes. |

## 4.4 View 2: CAS Perspective

The structure of the exploratory case study descriptions in this section is as follows:

1. Components of AMDIs
2. Data Governance
3. Environments of AMDIs
4. Behaviors of AMDIs

The various structures of each of the views are presented in the introduction of each section. The cases are described in the following order: National (RWS), Regional (Water Authority Delfland), and, finally, Local (Municipality of Rotterdam). At the end of the section, a comparison of the cases is provided.

### 4.4.1 LMW - Rijkswaterstaat

LMW demonstrates evolution as the current system was created by merging three previous existing, but separate monitoring networks: the Water Monitoring Network, which monitors inland waterways such as canals and rivers; the Monitoring Network North, which monitors North Sea oil platforms and channels; and the Zeeland Tidal Waters Monitoring Network which monitors the Zeeland delta waterways. LMW also includes data from third parties, including water data from foreign countries and other public organizations within The Netherlands. LMW is a mission-critical network which is vital to the national security of The Netherlands. This requires continuous and distributed monitoring and management. Security is therefore of vital importance to the LMW system, and RWS has ensured that redundancy is built into the system wherever possible to ensure continuance of service. As such this case shows the importance and complexity of managing and being aware of the rugged environments in which LMW is operating.

The complexity of LMW consists of, amongst others, the technical and organizational elements below. The network intelligence system is part of a mission critical circuit. Data is continuously measured and distributed. There is a rollout of local LMW functions at a large number of measurement locations where conditions may be location-specific. There is a tension between existing RWS sensors and external data requirements, on the one hand, and internal and external systems on the other. LMW operates on centralized software on virtual servers (VMWARE). RWS uses the following standard building blocks: Mule ESB, for the Mission Critical Chain Distribution Layer, and Ultimo which supports the configuration management of LMW, the building block, datacom for the Central LAN – WAN, Local data combination. LMW as a solution is encompassed within the Water domain architecture of RWS and is modular. In order to prevent trend failure, the method of converting raw sensor signals to measured values, including validations and conversion calculations, is prescribed in the RWS Internal (RMI) standard. The following requirements are important for RWS: reliability of sensor data; system availability (99.5%); level of effort for scalability of performance of the solution; product sustainability (functional technology and application management); degree of install-ability of local LMW features; automated testability of the chain, for both correct and incorrect situations.

There is also a high level of organizational complexity. It is required that the delivery of measurement data is guaranteed during the execution of any changes. There is a coordination of work between

different parties, for example, for the deployment of local LMW functions at the measurement locations it is necessary to include the services of the manager of the LMW Management and Maintenance Measurement Locations. Other organizational complexities include the fact that the RWS Technical Application Management (TAB Team) is forced to perform all development work in the production environment. System building blocks are managed by various external parties; and environments for testing and acceptance of new software are managed by an external party. Furthermore, the RWS CIV operates under certain quality assurance situations, including remote control of the supplier, with the most important management tool being a quality system of delivery.

The environment in which LMW operates is important as LMW provides a complete technical infrastructure for the gathering and distribution of water data and delivers the data to various stakeholders within and outside RWS such as the Storm Surge Barriers, hydro-meteorological centers, municipal port companies (among others Port of Rotterdam), flood early warning services and other private parties. As such, LMW monitors a wide variety of large water systems, from the North Sea and Wadden Sea to large rivers and canals such as the Maas and the Amsterdam-Rijn Canal. The monitoring system is therefore spread over a wide geographical area and monitoring stations can be found in the water, on land and on drilling platforms.

The cultural and political environment of RWS is also important, as attitude and behavior have a large impact on the development and quality of the system being maintained. Due to political and economic forces, RWS has undergone a large transition over the last ten years and has implemented an agency model, whereby much of the maintenance of the systems and the assets have be outsourced to external contractors. This has also been accompanied by an internal structural change in the organization whereby many people have been asked to change work locations and new teams have been formed. Business activities have been centralized, and the new business model has led to a number of reorganizations within the executive boards. As such, transparency and open communication within LMW as well as short lines of communication needed to be rediscovered. Attitude and behavior therefore remain underexposed. According to a number of interviewees, “some LMW processes were adjusted too quickly”. Interviewees suggested that “smaller contracts and a number of facility tasks should may have been better positioned with the line managers”. A lot of employees in business management came after centralization in a new workplace a customer focused approach was not always as well developed. But, still, the culture

of RWS has, for many years, been characterized by a desire to get things done and a certain pride in maintaining quality. As such, the culture at RWS is "to constantly strive to provide reliable management information, transparency, clear management lines and one central system". The traditional separation between engineer, manager and accountant is no longer visible. Departmental and district managers and project managers are fully responsible for content and budget. Transparency has now been implemented by clustering small projects, which simplifies control.

Water levels in shipping are closely monitored to ensure that ships of a certain class can traverse the shipping lanes. At periods of low water levels, for example, certain classes of ship have too deep a keel and would get stuck on the bottom. Also, if the water levels are too high, some classes of ships will not be able to pass under bridges. It has happened that ship captains misjudge the clearance of the bridge and collide with the bridge causing major structural damage. LMW provides, detailed, up to date data to help prevent this from happening. Clearances can be judged more finely and regulations can be made more efficient and can be more efficiently enforced.

LMW is a mission-critical registration. An Enterprise Architect at RWS called LMW one of the RWS core registrations. In the words of the Enterprise Architect, "if an organization is commissioned by RWS to build an asset, you would like to know where the asset objects are exactly, because they will be maintained by us in the future. We did not always receive that data automatically in the past. A contractor was required to send the bill to the RWS Purchasing Department. Sometimes the data needed for maintenance had to be collected after the project was completed."

Being a core registration, LMW provides RWS with operational efficiencies. LMW improves efficiency by reducing time in searching for the right dataset. LMW reduces the risk that data is hidden in the wrong file, reducing the risk of duplications, or incompleteness of data. At the time of writing, RWS was completing a project which mapped data registrations to the relevant business processes.

LMW also enables timely data with regards to the situation in rivers, canals and sea via sensors at approximately 640 monitoring sites. Monitoring sites are managed and administrated partly by RWS (approximately 300 physical measurement locations) but also partly by external parties (approximately 340 monitoring stations). The locations measured include hydrological and meteorological data. Conditions at the different measuring stations can be location specific. Meteorological data are collected in close collaboration with the Royal Netherlands

Meteorological Institute (KNMI). Hydrological data concerning the measurement of water levels, flow rate (average amount of water in m3/s), wave height and direction, velocity and direction and temperature. Also, in some locations water quality is measured in order to assess whether the water meets the norms of the European Union Water Framework Directive. Meteorological data concerning the measurement of wind speed and direction, air temperature and humidity, visibility, air pressure and cloud base is also collected. The LMW processes sensor information and upgrades this data to qualified readings. This case shows emergence as agents (people) within RWS have had to overcome massive interoperability issues presented by the technology used by standardizing the method of converting raw sensor signals to metrics. There are at least 30 different types of sensors used in the network. There are also several different types of external links to other organizations for the exchange of data, as well as large variety, volume and speeds of the data being collected. This is an internal RWS standard. By standardizing the method of converting raw sensor signals to metrics, including validations and conversion calculations LMW also displays dynamism, connectivity and adaptation.

### 4.4.2 BOS – Water Authority Delfland

Water Authority Delfland manages a complex water management system which includes a large number of assets. In order to gain benefits from IoT adoption, Water Authority Delfland has had to ensure that the quality of their master asset data system is of a sufficient quality to be able to link it to sensor based data. This has required significant levels of coordination to discover, document and implement data quality requirements. The Polder telemetry system contains all data and reads values via an OPC server from the ABB system and also alerts ABB values. The ABB system (800XA) is the telemetry system of the bosom mills. The ABB system reports continuous values via an OPC server to other systems, such as current flow rate (Q), alarm status, artwork status (KWan / off = Q> 0). Also, the signal can actively control the bosom mills from ABB to BOS; This is entered by the service provider. The OPC server is managed by ABB. BOS Delfland reads precipitation levels every 15 minutes and water levels on the bosom (measured at polder mills). In addition, BOS Delfland receives weather forecasts at MeteoConsult every 15 minutes via FTP. These are 3 files with 1-hour, 3-hour and 24-hour forecasts of precipitation (per hour), wind (per 3 hours) and evaporation (per day). The responsible level manager indicates which target level should be used (and at what time should be reached) and whether a

precipitation protocol is active; BOS then calculates the desired deployment of bosom mills every 15 minutes for the next 24 hours and, via the OPC server, sends a "request" for the ABB system for deployed ground for the current moment. Centrale storage is NETAPP FAS3140 in HA/cluster mode.

The complexity lies in the coordination of agents (people), and technology, as there are mixed ideas with regards to the responsibilities surrounding data management. Most interviewees reported conflicting ideas regarding roles and responsibilities. Often work is done ad hoc or, in the words of one official, through "data heroes". This is not experienced as being efficient. An example given is the creation of assets in the system when an error is found. It appears uncertain as to who should correct the data in the different systems, and often the work is done twice by "heroes", which often leads to differences in the various information systems. This has led to a lack of trust in the data. For example, officials reported that "reparations to the assets which have been made during the week, which need to picked up by another team over the weekend, need to be reflected in the data and the second team needs to be able to trust the data provide by the first team". As such, Water Authority Delfland has found it necessary to keep systems and registrations at a sufficient level of quality. But according to Water Authority Delfland officials the data management of the water system and the water chain is not yet completely mature and asset managers sometimes find it difficult to carry out its core tasks in an adequate and efficient manner. By establishing the strategic agreement "Water System and Water Chain", Delfland has committed to improving and maintaining data management. This case shows emergence in the following way: during the first quarter of 2013, Delft operated under the central direction of a Data Coordinator. But, as of September 1, 2012, an interim data coordinator was appointed to bridge the intermediate period until the data coordinator was in office. Team leaders began a "start-up", learning by regularly evaluating and, among other things, making inventories of the available data and making practical arrangements for delivering data for processing in the IRIS database and handling mutations in the data. Team leaders reported the bottlenecks they encountered, such as time, capacity and money, for which temporary practical solutions could be found.

According to officials at Water Authority Delfland, the data administrators discuss the information requirements with users in the primary processes, and decide on the data needs based on these discussions. Water Authority Delfland has made giant strides in the maturity of their data management processes, and there is an overriding

goal to continually make data "smarter", but the feeling expressed by a number of interviewees was that there are still many chances for improvement. The desire expressed by data managers was not necessarily to manage the asset objects themselves but instead to focus on managing the data entity, and to then act as a monitoring agent whereby maintenance work is outsourced to external parties. According to officials, Water Authority Delfland is still monitoring the asset object at a local level. If something changes to the object, they often do not feel the need to update the data, however, reports were made that this situation is improving greatly as people are becoming more aware of the need for data quality as improvements to asset management emerge through the use of data driven decision making. As such, effective communication is identified as being of importance to ensure that the data is made available and used to improve asset management processes.

Improved communication towards the citizen is also reported as being desirable. Data managers at Water Authority Delfland cite the example that complaints from citizens help to improve data quality. As such, participation from agents in the environment of the AMDI can have positive effects on the quality of the data. For example, if a permit (or denial of a permit) is questioned or objected to, it is important to be able to prove the correctness of the decision, which can only be done based on the data. IoT adoption has helped Water Authority Delfland to improve their asset management processes, but this improvement has had to emerge as people begin to trust the data.

IoT adoption has also helped Water Authority Delfland to empower citizens through opening the data to public use, and improving the ability of public citizens to notify Water Authority Delfland of discrepancies in current and past situations. This shows that the AMDI displays connectivity and dynamism. For example, in the Westland area, Water Authority Delfland makes resources available to farmers but the farmers manage the water flow and quality themselves. As such, Water Authority Delfland does not have physical control over the management of the assets, but maintain the supervision of the farmers through data analysis.

Water Authority Delfland officials recognize that releasing IoT data as open data is important for innovation, but the feeling is that it is hard to predict what the innovations may bring. Water Authority Delfland has a registry map ("leggerkaart") that shows all the water bodies managed by Water Authority Delfland. This is a legally binding document. But, conversely, Water Authority Delfland also has registers for permits that do not fit the official registry. It has happened that the official registry had to be adapted based on a separate agreement which meant that a

permit was given for the wrong area. Whilst quoting this example, officials also mentioned that awareness is greatly improved, but it remains a challenge to ensure that teams are sufficiently resourced and have access to the right knowledge. It remains a challenge to coordinate the teams, and much work is often based on collegiality. It was stated that data management is not seen as being exciting work by asset managers, but as awareness grows as to the potential benefits of IoT adoption, more and more improvements emerge within the asset management process.

### 4.4.3 Ground Water Measurement – Municipality of Rotterdam

Asset management activities at Rotterdam Municipality aim at controlling risk of facilities and systems failure. The maintenance and replacement plans are focused on reducing reduce risks to an acceptable level. All facilities for urban wastewater, storm water runoff and groundwater are analyzed using this method. By analyzing cause, consequence and failure mechanisms and quantifying these risks based on corporate values, insight is created as to the correct solution or management measure. Prioritization then takes place based on the severity of the risk and added value of the control measure. The functioning of the Rotterdam sewage system is initially theoretically determined. The starting point is rainfall with an intensity which occurs once every 2 years. Variables such as climate change, urban development, new construction and asset replacements are included. The calculations show how the system is expected to function, how much water the system can handle and how many flooding situations are theoretical possible. This case shows emergence as instruments to model the flow of rain water across the street and to portray the possible effects of measures are being developed. The calculations also describe environmental performance in each area, or how large the theoretical waste emission from the mixed sewage system is on surface water. This data is used by the water boards to test whether the theoretical waste emission from an overflow may cause issues for the water quality of urban water bodies. Rotterdam compares theoretical functioning with real-time sensor data. This comparison clarifies whether the theoretical calculations give a sufficiently accurate view of the system. Also, inspection data provides valuable information about the actual functioning of the sewage system. Complaints and notifications, inspection data and measurement data are combined to provide a complete picture of the actual functioning of the

sewage system. As such, this case shows how the improvement of asset management through IoT adoption emerges over time.

Waste water drainage inspections provide a comprehensive picture of the stability, drainage and water-tightness of the sewage system. Rotterdam municipality uses this information to plan repair and replacement work. There are two inspection methods: global (with video) or detailed (with driving camera). Evaluation of the inspections of gravity sewers takes place on the basis of the Dutch Standard NEN3398 (European Standard NEN-EN 13508-2). Since 1987, a total of about 67% of the gravity system has been inspected by means of well video inspection. Detailed inspections help determine the risk-driven approach. For asset management, detailed and up-to-date information is required about the state and operation of the entire system. The Exchange of Information Act (WION) obliges Rotterdam Municipality to maintain a current and complete database of sewage facilities. These serve to support and substantiate all executive tasks and management tasks. The most important tasks that the municipality performs for this purpose include periodically updating revision data (replacement and repair of sewerage, new construction and demolition). In addition to the requirements of the WION, the municipality currently maintains the sewage management database by entering and cleaning inspection data, and entering data in the management database with regards to wear and tear, outlets and boundaries of areas of measurement etc. During the planning period, Rotterdam municipality officials review how current and complete the sewage management database is and plans are made to further improve quality. In addition, Rotterdam stores data on the quality (inspection data) of the asset. This data is used by Rotterdam Municipality for multiple analyses, including the extent of possible early replacement of sewers. The facilitation and standardization of availability and access to data is becoming increasingly important, especially in the increasing cooperation in the waste water chain. Residents increasingly ask for insight into, for example, groundwater. Rotterdam provides information on the facilities for wastewater, rainwater and groundwater via the Internet and this data is linked to developments for efficient data management and system management.

Rotterdam municipality is a highly complex data infrastructure. The complexity can be found in the myriad of dependencies and integrations between systems which are managed by different teams and in different domains. Careful planning is therefore required during development. With regards to planning, Rotterdam Municipality employs enterprise architects who work in horizontal domains across departmental

silo's, but planning is also done in vertical domains by domain architects. Each domain strives to achieve the same level of quality in their information plans. This is done on a yearly basis. Eventually all project plans flow out of the year plan and are managed by the portfolio planner. Project prioritization is done based on the business plans which are developed by the business in the primary processes. Rotterdam officials state that a major challenge is ensure cohesion for individual domains. As such, all architects are members of the architectural board. Domain architects develop the architectures for their own domains and provide direction for the service providers of their particular domain. A challenge quoted by the domain architects is that "it is important to ensure that service providers are able to provide continuity of service whilst systems and data are being upgraded". The architecture board meets weekly in order to avoid system failure and ensure that all dependencies are accounted for.

### 4.4.4 Summary of View 2

This section compares the case studies with respect to view 2, and answers Research Question 2. Table 4-8 below summarizes the elements of AMDIs as identified in the three exploratory case studies. Table 4-8 also derives requirements for the design of the AMDI model.

Table 4-8: Elements of AMDIs and answer to research question 2a

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| Components | | | |
| Data<br><br>*Derived Requirements:*<br><br>-The AMDI model should describe all forms of IoT data included in the AMDI<br>- The AMDI model should describe all forms of metadata of IoT data in the AMDI | Multiple measurement data (e.g.):<br>-water temp.<br>-water depth<br>-wave height<br>-wind speed | Realtime measurements from Delfland telemetry, Measurements (e.g.):<br>-water levels,<br>-met-information<br>-flow rates | Measurements indicate the groundwater level relative to NAP. |

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| Technology<br><br>*Derived Requirements:*<br><br>- The AMDI model should describe the technical infrastructure which enables the AMDI<br>- The AMDI model should describe the application landscape which enables the AMDI | Multiple sensor and messaging types (e.g.)<br>RJ45 Ethernet, across different media, such as DSL, UMTS, RAM mobile. | Values read via a server from the telemetry system of the water mills | Automatic pressure sensors consist of an electronic pressure sensor coupled to a data logger, which registers the measured hydrostatic pressure at a given frequency. |
| Agents<br><br>*Derived Requirements:*<br><br>- The AMDI model should describe the human and organizational agents driving the AMDI<br>- The AMDI model should describe the technological agents driving the AMDI | Multiple agents and varying levels (e.g.)<br>-International orgs.<br>-National orgs.<br>-Internal divisions. | Multiple agents and varying levels (e.g.)<br>-Meteorology orgs.<br>-Internal departments | Multiple agents and varying levels (e.g.)<br>-Meteorology orgs.<br>-Internal departments |
| Data Governance (see view 3 for in-depth analysis) | Contract forming between IT org. and Water Management org. Water Management org. is data owner | Self-governing operational data management via data managers and IT department. | Self-governing operational data management via data managers and IT department. |
| Environments | | | |
| Physical<br><br>*Derived Requirements:*<br>- The AMDI model should describe the physical environment | -Very large area (country-wide)<br>-Multiple large waterway types - Seas, Large and small rivers, canals etc. | -Large area (multiple municipalities)<br>-Multiple small waterway types such small and medium canals, and small rivers | -Middle-large area<br>-Mostly sewerage systems |

| **Concept** | **Case Studies** | | |
|---|---|---|---|
| | ***LMW - RWS*** | ***BOS - Water Authority Delfland*** | ***Ground Water Measurement – Municipality of Rotterdam*** |
| within which the AMDI is located<br>- The AMDI model should describe how the physical environment affects the AMDI | | | |
| Cultural<br><br>*Derived Requirements:*<br>- The AMDI model should describe the cultural environment within which the AMDI is located<br>- The AMDI model should describe how the cultural environment affects the AMDI | Transparent, "get things done" attitude, but also adjustment to new ways of working and new organizational structures which blurs lines of responsibility. | The flexibility and robustness required realize the necessary adjustments has proved to be a core quality. | Rotterdam is known as a city with a "don't just talk, but get the job done" attitude. |
| Political<br><br>*Derived Requirements:*<br><br>- The AMDI model should describe the political environment within which the AMDI is located<br>- The AMDI model should describe how the political environment affects the AMDI | Move towards agency forming whereby much of the maintenance work is outsourced, causing necessary changes to ways of working. | Delfland operates largely independently, but budget and strategic policy is set by the elected officials. | Move towards agency forming whereby much of the maintenance work is outsourced, causing necessary changes to ways of working. Budget and strategic policy is set by the elected officials. |

Table 4-9 below summarizes the behaviors of asset management data structures as identified in the three exploratory case studies. Table 4-9 also derives requirements for the AMDI model design.

Table 4-9: Behaviors of AMDIs and answer to research question 2b

| **Concept (Literature)** | ***Case Studies*** |
|---|---|
| Dynamism<br><br>*Derived Requirements:*<br><br>- The AMDI model should accommodate dynamism of elements within the AMDI | *LMW – RWS*<br>The number of agents, their interdependence, and their openness to external influences, changes constantly and discontinuously. Constant change in LMW is driven by the number of agents, their association with their own rules of behavior and the interdependence between the agents and their environments. For example, as RWS moves towards agency forming and restructures the organization accordingly, management and maintenance of the system is more and more outsourced, and new techniques are introduced. |
| | *BOS - Water Authority Delfland*<br>The number of agents, their interdependence, and their openness to external influences, changes constantly and discontinuously. Constant change in BOS is driven by the number of agents, their association with their own rules of behavior and the interdependence between the agents and their environments. For example, IoT adoption has also helped Delfland to open the data to public use, improving the ability of public citizens to notify Delfland of discrepancies in current and past situations. In the Westland area, Delfland makes resources available to farmers but the farmers manage the water flow and quality themselves. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>The number of agents, their interdependence, and their openness to external influences, changes constantly and discontinuously. Constant change in BOS is driven by the number of agents, their association with their own rules of behavior and the interdependence between the agents and their environments. For example, Rotterdam Municipality has a highly complex data infrastructure. The complexity can be found in the myriad of dependencies and integrations between systems which are managed by different teams and in different domains. |
| Connectivity<br><br>*Derived Requirements:*<br><br>The AMDI model should demonstrate connectivity | *LMW – RWS*<br>The diversity of skills, strategies and rules of different agents within LMW means that it is difficult for a single agent to become more useful in an isolated context, so there is a constant exchange of information and needs between the components and the actors in the system. The relationships are complicated and massively entangled because the components are numerous and highly interrelated. For example, the network intelligence system is part of a mission critical circuit. Data is continuously measured and distributed. There is a rollout of local LMW functions at a large number of measurement locations where conditions may be location-specific. There is a tension between existing RWS sensors and external data requirements, on the one hand, and internal and external systems on the other. |
| | *BOS - Water Authority Delfland*<br>The diversity of skills, strategies and rules of different agents within BOS means that it is difficult for a single agent to become |

| **Concept (Literature)** | ***Case Studies*** |
|---|---|
| | more useful in an isolated context, so there is a constant exchange of information and needs between the components and the actors in the system. The relationships are complicated and massively entangled because the components are numerous and highly interrelated. For example, data administrators discuss the information requirements with users in the primary processes, and decide on the data needs based on these discussions, but Delfland still needs people to validate the data, despite the automation of the data collection through the application of sensors. In the field, especially in a densely populated area, the asset infrastructure is changing constantly, as assets are replaced and renewed and these changes need to be reflected and validated in the system to ensure that the system reflects the situation on the ground. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>The diversity of skills, strategies and rules of different agents within the groundwater measurement network means that it is difficult for a single agent to become more useful in an isolated context, so there is a constant exchange of information and needs between the components and the actors in the system. The relationships are complicated and massively entangled because the components are numerous and highly interrelated. For example, project prioritization is done based on the business plans which are developed by the business in the primary processes, but Rotterdam officials state that it is a major challenge to cohesion for individual domains. |
| Adaptation<br><br>*Derived Requirements:*<br><br>- The AMDI model should accommodate adaptations within the AMDI | *LMW – RWS*<br>The adaptive behavior of LMW is the result of a strategy which combines exploration to maintain diversity, and exploitation to reinforce promising tracks. For example, business activities have been centralized, and the new business model has led to a number of reorganizations within the executive boards. As such, transparency and open communication within LMW as well as short lines of communication needed to be rediscovered. |
| | *BOS - Water Authority Delfland*<br>The adaptive behavior of BOS is the result of a strategy which combines exploration to maintain diversity, and exploitation to reinforce promising tracks. For example, Delfland team leaders began a "start-up", learning by regularly evaluating and, among other things, making inventories of the available data and making practical arrangements for delivering data for processing in the IRIS database and handling mutations in the data. Team leaders reported the bottlenecks they encountered, such as time, capacity and money, for which temporary practical solutions could be found. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>The adaptive behavior of the groundwater measurement network is the result of a strategy which combines exploration to maintain diversity, and exploitation to reinforce promising tracks. For |

| **Concept (Literature)** | ***Case Studies*** |
|---|---|
| | example, Rotterdam compares theoretical functioning with real-time sensor data. This comparison clarifies whether the theoretical calculations give a sufficiently accurate view of the system. Also, inspection data provides valuable information about the actual functioning of the sewage system. Complaints and notifications, inspection data and measurement data are combined to provide a complete picture of the actual functioning of the sewage system. |
| Emergence<br><br>*Derived Requirements:*<br><br>- The AMDI model should accommodate emergence of behaviors within the AMDI | *LMW – RWS*<br>In the LMW system, order emerges as agents govern their own rules of behavior and adapt to their environment. Formal order is not externally imposed from outside of LMW, but rather emerges from interactions between agents. For example, agents (people) within RWS have had to overcome massive interoperability issues presented by the technology used by standardizing the method of converting raw sensor signals to metrics. There are at least 30 different types of sensors used in the network. There are also several different types of external links to other organizations for the exchange of data, as well as large variety, volume and speeds of the data being collected. |
| | *BOS - Water Authority Delfland*<br>In the BOS system, order emerges as agents govern their own rules of behavior and adapt to their environment. Formal order is not externally imposed from outside of BOS, but rather emerges from interactions between agents. For example, if a permit (or denial of a permit) is questioned or objected to, it is important to be able to prove the correctness of the decision, which can only be done based on the data. IoT adoption has helped Water Authority Delfland to improve their asset management processes, but this improvement has had to emerge as people begin to trust the data. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>In the Groundwater measurement system, order emerges as agents govern their own rules of behavior and adapt to their environment. Formal order is not externally imposed from outside of the measurement system, but rather emerges from interactions between agents. For example, instruments to model the flow of rain water across the street and to portray the possible effects of measures are being developed. The calculations also describe environmental performance in each area, or how large the theoretical waste emission from the mixed sewage system is on surface water. This data is used by the water boards to test whether the theoretical waste emission from an overflow may cause issues for the water quality of urban water bodies. |

## *4.5* View 3: Data Governance Perspective

The structure of the exploratory case study descriptions with regards to view 3 is as follows: first the data management organization is discussed, then the alignment mechanisms, then the compliancy mechanisms and finally the clarification mechanisms. The cases are described in the following order: National (RWS), Regional (Water Authority Delfland), and, finally, Local (Municipality of Rotterdam). At the end of the section, a comparison of the cases is provided.

### 4.5.1 LMW - Rijkswaterstaat

According to a RWS Domain Architect, RWS wants to work in a process-oriented manner. If RWS invests well in all processes, RWS does its job well. As such, all development work at RWS is performed under architecture and a domain architect has been allocated to each process. There are three architect roles defined to shape the architecture. Enterprise Architects monitor the global RWS architecture; Domain Architects focus on a specific process; and Solution Architects focus on projects and describe the concrete solutions. RWS architects believe that the data frame should be implemented at a project level, so that the solution architect can take care of the actual implementation. Domain architects are at the center of the process. All domain architects have been assigned to the process-oriented departments, in the case of LMW that would be Water Management. The Department of Data Collection and Analysis (IGA) manages all data for all processes. There is an architecture meeting, chaired by the enterprise architects, where all processes are held together that overlook the entire organization. The Department of Strategy and Policy also has the task of implementing works under architecture. There must be a coherent whole of applying the data frames across all domains. If something goes wrong, the CIO can intervene.

LMW used to be one department within RWS that was responsible for the entire management chain, but is now divided into 10 or 12 departments, for example "Sensors" and "DataCom". Several of the interviewees at RWS noticed that “communication between departments is very difficult, which means that problem management can become problematic as finding the right people involved can be difficult”. RWS therefore decided to include an extra role in the management chain – the process director. The process director has a (virtual) team of people around them from each separate department. As such, data management and functional management falls under their control. RWS also has a Quality and Configuration department that checks the data quality

according to the validation rules. In the past, managing the LMW assets was performed by RWS, but since July 1 2015, the management of the assets was conducted under System-Based Contract Management (i.e., all maintenance work was outsourced). There are weekly operational planning meetings and monthly tactical planning meetings.

With regards to LMW, users submit their wishes and requirements to the Water, Traffic and Environment (WVL) Department. For example, with regards to managing a new lock, the prevailing water levels are usually requested. WVL submits such a request to the Central Information Department (CIV) with the question: can you offer that service? The development services department of the CIV will then assess the request. If it is decided that LMW is the best source, LMW will give an in-depth advice to the requester about what is necessary to be able provide this data. WVL annually formulates a Program of Requirements which states exactly what RWS needs to deliver, with what quality and what availability, and the Process Director ensures that the chain is managed in such the way as RWS can offer it. As way of example, one of the interviewees cited an example of the nautical administrator in the region who might say, "I want to have a channel there", or, "The channel must be wider or deeper". This requires a change to the network. The Large Projects Department (GPO) is ordered to realize this. However, RWS also wants to keep the data on the network up to date, so the nautical administrator in the region needs to modify the data, or create an assignment. The interviewee stated that "at RWS, data ownership must be where data is created". Often, there may be the realization that one is responsible for the data, but there is often an indication that there is no budget or there are not enough people to perform the task.

Once the service has been developed, the Quality and Configuration department then assesses whether the data RWS provides complies with the quality requirements. The Program of Requirements is updated every year. WVL's questionnaire team then validates the requirements: "are they still required, is the quality still good?" This supplements the Program of Requirements and extends it. This approach also makes it possible to better match the delivered frequency and precision of data to the current needs of data carriers. This provides room for differentiation in deploying measurement stations. Another step further is the 'lighter' execution of the measuring systems. RWS considers the LMW system to be very well maintained. From the perspective of the Process Director, RWS is more inclined to maintain the existing layout and, if necessary, apply patches to keep the system running, rather than introduce innovations.

LMW is engaged in the collection of water data from rivers and the North Sea (water levels, wave height, wave direction, chloride levels, oxygen, etc.). The data is used within RWS, but also by external parties, for example by the Royal Dutch Meteorological Institute (KNMI), and by municipal port companies. The purpose of LMW is to formulate expectations and, among other things, make decisions about opening and closing of doors and for water level management. RWS has a well-developed data access network which allows access to users based on open standards. Although it creates and manages its metadata locally, RWS also makes use of external facilities to publish its data. For example, RWS uses the National Spatial Data metadata library, National Geo-Register (NGR) to publish and find its spatial data. Other data types are generally stored in specialized systems such as digital libraries for images and digital photography. The metadata for these data types is created, stored and searched within the system itself. There are also several different types of external links to other organizations for the exchange of data. With regards to its data, RWS has implemented a variety of open standards in order to maintain compliance to external policies and directives, but they have also implemented de facto, industrial standards where necessary. The implementation of open standards appears to be driven by compliancy constraints, whereas the implementation of industrial standards appears to be driven by performance necessity. For example, as LMW is a mission-critical network which is vital to the national security of The Netherlands, continuous and distributed monitoring and management is required. As security is of vital importance to the LMW system, RWS has ensured that redundancy is built into the system wherever possible to ensure continuance of service.

The distribution of data greatly improves the transparency of the decisions and advice given by RWS such as when to close the storm surge barriers or when certain waterbodies are restricted to public access. Citizens have been empowered to decide where and when they wish to swim in open water, as the water quality of open water bodies is now publicized. LMW has greatly contributed to the advanced forecasting of water levels and the monitoring of trends. But, LMW also includes data from third parties, including water data from foreign countries and other public organizations within The Netherlands. RWS is restricted from sharing externally created LMW data with other third parties due to requirements imposed on them by the participating parties.

### 4.5.2 BOS – Water Authority Delfland

At Water Authority Delfland, data management is generally operationalized within the department "Data Management". This department provides the tools that facilitate the data management process. These products are realized and coordinated by the data coordinator. The data is managed (partly) by the data administrators. The data service desk also shares some data management responsibilities. The data service desk publishes data reports on errors and changes. The service desk also maintains guidelines for data usage: where can you find what, what do you do in certain situations, etc. In addition, the service desk maintains the data dictionary (unambiguous definitions), the development calendar and manages manuals and protocols.

The data development calendar is an instrument that provides insight into what data is being collected. The data administrator determines which developments can be matched and combined. Employees are required to report all developments and report them on the development calendar, so developments can be combined and planned more efficiently. Part of the development calendar is the "Recovery Protocol" and the "Program of Requirements". The "Inventory Protocol" describes how the data development process works, who needs to be included, how the development calendar works, and where results should be submitted, etc. The Requirements Program contains the measurement parameters, formats, and the technical requirements to be used when measuring data. The data dictionary contains the definitions of the data from the minimum set. In addition, various specifications of objects and features are included. The data administrators determine the contents of the data dictionary. Delfland's data dictionary includes, as far as possible, the national standards (including Aquo and DAMO). In addition to internal policies, the frameworks are formed by National and European rules and standards, such as the National Base Registrations (e.g. BGT), Inspire, and the European Water Directive. These frameworks are described in the Data Management Plan and are monitored by the data coordinator. At Water Authority Delfland, the main role of the data owner is to ensure that data management is implemented according to plan and to facilitate data management activities, enabling budget and resources. Once budget decisions have been made at the strategic level, the role of tactical management is to coordinate data management activities and to achieve data (quality) requirements. Challenges acknowledged by officials at Water Authority Delfland include identifying the correct data owner. The same data sources are often used and maintained within different primary processes, and a clear data owner is

not always obvious. This makes releasing budget and capacity for data management activities sometimes difficult.

The main role of the tactical data manager is to translate strategic goals into operational activities and objectives. As such, many of the operational data management activities at Water Authority Delfland are organized within projects. Within the projects, roles are divided between the data manager, the data administrator and the data owner. The difference between the data owner and the data administrator is that the data owner is often a tactical line manager, and has a coordinating role, whereas the data administrator is operational and manages the data itself. As such, the data management function at Water Authority Delfland is reasonably self-governing. Tactical managers tend to have a shared responsibility and divide the responsibilities amongst themselves. Interviewees report that there is quite some fragmentation with regards to data management across the organization, but that issues are normally resolved amongst the managers in a collegial, team fashion. In the words of a Water Authority Delfland manager, "Data is created across the whole organization and so the process requires people from throughout the organization to get involved and take responsibility. The polder model, with coordination, works well!" Tactical line managers at Water Authority Delfland rely on the professionalism of their staff and once they have provide the process format and have mapped the dependencies tactical managers are confident that the process runs to a high level of quality.

### 4.5.3 Ground Water Measurement – Municipality of Rotterdam

Rotterdam Municipality has a systematic data governance structure in place. Administration of digital maps as data (registrations) and systems for automated distribution to internal and external clients is performed by the Department of City Development at Rotterdam Municipality. The data management process is coordinated by a process manager whose responsibility includes the data registration within his or her portfolio. The process manager manages effects of changes to registries (data), changes to the delivery systems and changes to the client applications. The process manager is not responsible for the management of the base registrations (such as the large scale topography, "BGT"), but organizes the coordination of product quality. For example, bus stops used to be registered in GIS systems as lines and planes, but are now registered as points. This has consequences for the client applications. As portfolio holder, the process manager indicates requirements, with costs, for the

annual development plan. Interviewees reported that processes tend to be kept small and informal which allows processes to flow better. Data management projects are often differentiated in three groups: 1) Group preparation; 2) Group business processes; and 3) Group communication to clients.

A lack of efficient communication is reported as being a long standing issue. According to Rotterdam officials, "communication used to be unidirectional, from the provider to the user which often led to frustrations". But interviewees report that "the introduction of user groups has improved the situation considerably". When errors or complaints are reported by the users, the process manager does an initial check to clarify the cause of the issue, as once the fault is reported to ICT, the process becomes formalized. However, this process is not experienced as being an optimal solution and it does not have a standardized solution procedure as it relies on a best effort mentality. For example, if the process manager is absent, problems may arise. Interviewees suggested that there is pressure on capacity and processes are often not documented. Much of the local knowledge remains with individuals which can cause disruptions if the individual is not present. As such, problem management is often reactive. But despite the lack of overall data management framework, the process felt to be relatively stable. The groups are small which allows for fast reaction times.

Although governance is in place, interviewees did report that "discussions regarding systems or changes to the data can be challenging due to a silo mindset". Changes in the data can have significant effects on processes and clients, with dissatisfied users as the result. When changes are required to data systems, asset managers address proposals to "City Development", and policy employees at 'City Development' make estimations of the potential impact on the systems. Final responsibility for prioritization and acceptance of changes lies with the Director of City Development. The CIO is responsible for developing the data strategy, but a number of interviewees remarked that "little true effect of the data strategy was felt at the operational level due to multiple management layers between the CIO at the strategic layer and the operational layer". As such, current proposed changes are often much smaller than those previously made. For example, recent reorganizations have centralized data management, but previously data management was fragmented in management regions with little central control over information. Local knowledge of the data was at a premium which meant that local asset managers were able to receive exactly what they wanted, whenever they wanted it. Centralizing data management meant that asset managers

needed to conform to generic processes which has led to dissatisfaction in certain situations.

Data managers at Rotterdam Municipality believe that the data is of a high quality, although there are sometimes differences in the details and how people interpret the data. Interviewees reported that "there was a high level of awareness of data quality needs at Rotterdam Municipality which meant that operational checks are performed constantly during operations in an informal way and people assume individual responsibility for the data". For example, quality checks on data are made partly by own personnel, and partly external hires. There is an existing format for quality inspections, including subjective scales. However, subjective scales can differ depending on the inspector, and as such, data quality management remains relatively reactive, with a number of interviewees expressing the desire to be able to quantify data quality to be certain of the quality of the data they are managing. In the words of one interviewee, "I want to able to measure the quality of the data without physically going to the assets. What is poor data? It is a luxury to be able to send people to check if data corresponds to reality. For geometry we are dependent on 'base information', and enrichment with digital communication data when changes occur."

The changes mentioned above include changes to the asset infrastructures performed by subcontractors. Officials at Rotterdam Municipality believe that subcontractors often prefer to pay fines than to provide the data about the replaced or renovated asset. Inspections of data provided by subcontractors remain informal, although with the inclusion of service level agreements which include provisions for data such as a data delivery agreement, informal lines are beginning to dissipate. However, trust (in the professionalism of co-workers and contractors) is an important part of the data management process. People remain uncertain of their responsibilities, but trust each other to get the job done.

### 4.5.4 Summary of View 3

This section compares the case studies with respect to view 3, and answers Research Question 3. Table 4-10 below compares the three exploratory case studies. Table 4-10 also derives requirements for the AMDI model design.

Table 4-10: Comparison of the data governance of the case studies and answer to research question 3

| **Data Governance Concept** | ***Case Studies*** |
|---|---|
| *Organizational capability*<br><br>*Derived Requirements:*<br><br>- The AMDI model should describe the ownership and stewardship of data within the AMDI<br>- The AMDI model should improve coordination of decision making with regards to data management | *LMW – RWS*<br>Organization of data management at LMW improves coordination of decision-making by separating duties and concern through the balancing of roles and definition of decision rights. For example, all development work at RWS is performed under architecture and a domain architect has been allocated to the LMW process. There are three architect roles defined to shape the LMW architecture. Enterprise Architects monitor the global architecture; Domain Architects focus on specific processes in LMW; and Solution Architects focus on projects and describe the concrete solutions. |
| | *BOS - Water Authority Delfland*<br>Organization of data management at BOS improves coordination of decision-making by separating duties and concern through the balancing of roles and definition of decision rights. For example, at Delfland data management is generally operationalized within the department "Data management". This department provides the tools that facilitate the data management process. These products are realized and coordinated by the data coordinator. The data is managed (partly) by the data administrators. The data service desk also shares some data management responsibilities. The data service desk publishes data reports on errors and changes. The service desk also maintains guidelines for data usage: where can you find what, what do you do in certain situations, etc. In addition, the service desk maintains the data dictionary (unambiguous definitions), the development calendar and manages manuals and protocols. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>Organization of data management at Rotterdam improves coordination of decision-making by separating duties and concern through the balancing of roles and definition of decision rights. For example, Rotterdam Municipality has a systematic data governance structure in place. Administration of digital maps as data (registrations) and systems for automated distribution to internal and external clients is performed by the Department of City Development at Rotterdam Municipality. The data management process is coordinated by a process manager whose responsibility includes the data registration within his or her portfolio. The process manager manages effects of changes to registries (data), changes to the delivery systems and changes to the clients. |
| *Alignment*<br><br>*Derived Requirements:* | *LMW – RWS*<br>Developing a data strategy and defining data quality requirements helps LMW meet business needs by reducing error of use and establishing effective policies and procedures. For example, With regards to LMW, users submit their wishes and |

| | |
|---|---|
| - The AMDI model should align business data needs with data capabilities provided by the AMDI<br>- The AMDI model should include processes to develop a data strategy | requirements to the Water, Traffic and Environment (WVL) Department. WVL then submits a request to the Central Information Department (CIV) to fulfill the requirement. The development services department of the CIV will then assess the request. If it is decided that LMW is the best source, LMW will give an in-depth advice to the requester about what is necessary to be able provide this data. WVL annually formulates a Program of Requirements which states exactly what RWS needs to deliver, with what quality and what availability, and the Process Director ensures that the chain is managed in such the way as RWS can offer it. Once the service has been developed, the Quality and Configuration department then assesses whether the data RWS provides complies with the quality requirements. |
| | *BOS - Water Authority Delfland*<br>Developing a data strategy and defining data quality requirements helps BOS meet business needs by reducing error of use and establishing effective policies and procedures. For example, The BOS Requirements Program contains the measurement parameters, formats, and the technical requirements to be used when measuring data. The data dictionary contains the definitions of the data from the minimum set. In addition, various specifications of objects and features are included. The data administrators determine the contents of the data dictionary. The Delfland's data dictionary includes, as far as possible, the national standards (including Aquo and DAMO). |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>Due to a lack of effective policies and procedures, Rotterdam has challenges with meeting needs. When errors or complaints are reported by the users, the process manager does an initial check to clarify the cause of the issue, as once the fault is reported to ICT, the process becomes formalized. However, this process is not experienced as being an optimal solution and it does not have a standardized solution procedure as it relies on a best effort mentality. For example, if the process manager is absent, problems may arise. There is pressure on capacity and processes are often not documented. Much of the local knowledge remains with individuals which can cause disruptions if the individual is not present. As such, problem management is often reactive. |
| *Compliance*<br><br>*Derived Requirements:*<br><br>- The AMDI model should define accountability with regards to data management and data use<br>- The AMDI model should help enforce | *LMW – RWS*<br>Enforcing policy and ensuring accountability through due diligence helps LMW protect citizen privacy and the security of the system, whilst allowing RWS to open the data to the general public. For example, as LMW is a mission-critical network which is vital to the national security of The Netherlands, continuous and distributed monitoring and management is required. As security is of vital importance to the LMW system, RWS has ensured that redundancy is built into the system wherever possible to ensure continuance of service. |
| | *BOS - Water Authority Delfland*<br>Enforcing policy and ensuring accountability through due diligence helps BOS protect citizen privacy and the security of |

| | |
|---|---|
| policies regarding data management | the system, whilst allowing Delfland to open the data to the general public. For example, employees are required to report all developments and report them on the development calendar, so developments can be combined and planned more efficiently. Part of the development calendar is the "Recovery Protocol" and the "Program of Requirements". The "Inventory Protocol" describes how the data development process works, who needs to be included, how the development calendar works, and where results should be submitted, etc. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>At Rotterdam, changes in the data can have significant effects on processes and clients, with dissatisfied users as the result. When changes are required to data systems, asset managers address proposals to "City Development", and policy employees at 'City Development' make estimations of the potential impact on the systems. Final responsibility for prioritization and acceptance of changes lies with the Director of City Development. |
| *Clarification*<br><br>*Derived Requirements:*<br><br>- The AMDI model should develop a shared data commons<br>- The AMDI model should standardize operational processes | *LMW – RWS*<br>Good metadata management and standardized data models and operational processes facilitates communication by ensuring a shared data commons. For example, RWS has implemented a variety of open standards in order to maintain compliancy to external policies and directives, but they have also implemented de facto, industrial standards where necessary. The implementation of open standards is driven by compliancy constraints, whereas the implementation of industrial standards appears is driven by performance necessity. |
| | *BOS - Water Authority Delfland*<br>Good metadata management and standardized data models and operational processes facilitates communication by ensuring a shared data commons. For example In addition to internal policies, the frameworks used within BOS are formed by National and European rules and standards, such as the National Base Registrations (e.g. BGT), Inspire, and the European Water Directive. These frameworks are described in the Data Management Plan and are monitored by the data coordinator. |
| | *Ground Water Measurement – Municipality of Rotterdam*<br>Good metadata management and standardized data models and operational processes facilitates communication by ensuring a shared data commons. For example data managers at Rotterdam Municipality believe that the data is of a high quality, although there are sometimes differences in the details and how people interpret the data. Interviewees reported that there was a high level of awareness of data quality needs at Rotterdam Municipality which meant that operational checks are performed constantly during operations in an informal way and people assume individual responsibility for the data. |

## 4.6 Conclusions

From a design science approach, the exploratory case studies combined with the literature review form the foundation of the knowledge base from which requirements for the artefact are defined. This chapter outlines and describes the three exploratory case studies from three different vantage points, or views. The first case study, at a national level, was that of water management at Rijkswaterstaat utilizing the National Water Measuring Network (LMW). The second case study, at a regional level, was that of water management at the Water Authority Delfland, utilizing the decision support system, BOS. The third case study, at a local level, was that of water management at the Municipality of Rotterdam, utilizing the ground water measuring network. The first view taken of each of the case studies was that improving achieving the expected benefits of asset management through IoT often carries unexpected risks. The second view taken of each case was that the asset management through IoT emerges through the complex interaction of data, agents, and technology. The third view taken of each case study was that asset management through IoT requires coordination of the complex interaction of agents, data and technology by means of data governance.

The exploratory case studies show that adoption of IoT has driven an explosive growth in data. Within the three case studies IoT is used in asset management in a variety of ways related both to the real-time measurement of the quality of assets and analyses of data as to trend analysis of historical data over time to reduce maintenance costs. This research shows that IoT data may be used at the strategic, tactical and operational levels of asset management. The results of the case studies also demonstrate that the three expectations of how IoT will affect asset management identified in the literature review are also revealed in the field. IoT has been seen to change performance measurement of infrastructure services, due to, for example, predictive analytics. Second, IoT adoption changes the perception of users of infrastructure services of how asset management organizations perform, like the deterioration of the quality of assets over time. Finally, IoT has been seen to change improvement processes, for example through self-organizing resource planning. The case studies also demonstrate that automation of data capture makes manual intervention unnecessary and results in a large amount of data. Making this data publicly available as in the LMW case enables organizational transparency, helping to ensure proper oversight and reducing waste. The exploratory cases show that enabling self-service in this way empowers asset managers to make data driven decisions by making use of the vast amount of data available to them. As such, the

cases show that IoT makes it possible for an asset management organization to be more situational aware, increasing service flexibility and service effectiveness and driving business transformation processes. In essence, the benefits of asset management through IoT are derived from the timely availability of large amounts of data which is automatically collected and readily shareable. However, the exploratory cases also show that both technological and organizational challenges need to be addressed to order to be able to achieve the benefits that IoT adoption can bring. The cases reveal that important risks of asset management through IoT are related to data ownership, security, privacy and sharing of information. Disclosure of user data could reveal sensitive information such as personal habits or personal financial information and unauthorized access to this information can severely impact user privacy. For example, ground water data can have negative impacts on housing prices. As such, the exploratory case studies demonstrate that the lack of convincing solutions for access control hinders the adoption of IoT in applications when dealing with sensitive data. *As such the results of the case studies complete the answer to research question 1 which asks how can IoT improve asset management*?

The exploratory cases confirm that AMDIs consist of relatively stable and simple components. This research has identified three essential components of AMDIs, namely data, agents and technology. The exploratory case demonstrate that the largest benefits of IoT adoption in asset management are provided by the data generated by IoT, but the cases also underline the importance of metadata to provide context and thus make the usable as information. This implies that proper metadata maintenance is essential if asset management organizations are to gain full benefits from IoT. The exploratory cases also underline the fact that technology is an important enabler of AMDIs and can be further separated into hardware, the collection of physical components that constitute an information system, and software, that part of an information system that consists of computable instructions. The exploratory cases also show that these classifications can be further refined to explicitly define layers of technology which can be used by architects to design the technological systems.

However, the exploratory cases also show that agents are explicitly essential for successful IoT adoption in asset management. People are seen as a key element in AMDIs as people are responsible for the decision making, design, implementation, and use of the data infrastructure. But significantly, artificial intelligence is becoming more and more prevalent in service oriented environments as witnessed by the intelligence of the

LMW system. This implies that artificial intelligence and robotics as agents are beginning to play an important role in the development of data infrastructures as more and more infrastructure management processes become automated.

This simultaneous interaction of agents, data and technology within the cases has forced an emergent behavior. For example, combining data between multiple systems in the LMW has created greater insights than simple analysis on a single system would have. The diversity of skills, experiments, strategies and rules of different agents within the exploratory case studies have ensured their dynamic adaptive behavior which was observed over time. The case studies therefore show that AMDIs, as CASs, are dynamic, and because of the number of agents, their interdependence, and their openness to external influences, changes constantly and discontinuously. *As such the results of the case studies complete the answer to research question 2 which asks what are the elements and behaviors of AMDIs that enable asset management through IoT*?

The exploratory case studies confirm the identification of data governance as embodying the schema of AMDIs. Data governance is shown in the exploratory cases as defining how the components of AMDIs (data, technology, agents) interact. The cases show that data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data, ensures that data is aligned to the needs of the organization, monitors and enforces compliancy, and ensures a common understanding of the data throughout the organization. The exploratory case studies demonstrate that new sources of data, originating from IoT, provide new insights to help asset management organizations face ever changing challenges. But the case studies also demonstrate that data must be of sufficient quality in order to be acted upon and too much data can create "noise" which detracts van the quality of the information. Having AMDIs which produce data of a quality that is aligned to the needs of the organization is essential for asset management organizations which rely on data-driven decision-making processes. *As such the results of the case studies complete the answer to research question 3 which asks what are the elements of data governance in AMDIs that enable asset management through IoT?*

# Chapter 5 Design of the AMDI Model

*"What you have said,*
*I will consider; what you have to say*
*I will with patience hear; and find a time*
*Both meet to hear and answer such high things."*
**- William Shakespeare (Julius Caesar: Act-I, Scene-II)**

## 5.1 Introduction

In Chapter 4 we presented the results of three exploratory case studies in which asset management through IoT plays a central role. The exploratory case studies confirm the duality of IoT in asset management and also confirm the necessity of viewing AMDIs as CAS when adopting new technologies such as IoT. The results of the case studies fill important gaps in our knowledge base such as, for example, the insight that IoT adoption makes it possible for an asset management organization to be more situational aware, increasing service flexibility and service effectiveness and driving business transformation processes, but, at the same time, also introduces risks related to data ownership, security, privacy and sharing of information which force changes to the asset management organization. In this way, the case studies provide us with the requirements needed to be able to design a model of AMDIs so that these previously unforeseen risks and changes can be accommodated.

The main goal of this Chapter is therefore to define the requirements, design propositions and design principles which constrain the design of the AMDI. These are tested in Chapter 7 according to tests defined in Chapter 2, section 2.4.5. Requirements define what the designed model will eventually look like, and, as such, completes the answers to Research Questions 1 through to 3, as well as partially answering Research Question 4. According to Buede (2009), the requirements for a system set up standards and measurement tools for judging the success of the system design. As such, the requirements defined below act as input for judging the success of the AMDI model in

improving asset management. These requirements are assessed in Chapter 7 in the test cases. Sections 5.2, 5.3, and 5.4 define the requirements of the AMDI model. Figure 5-1 below shows that, having expanded the knowledge base through exploratory case studies in Chapter 4 to fill knowledge gaps identified in the literature review (Chapter 3), Chapter 5 introduces the relevance cycle in which the requirements of the AMDI model are defined based on the findings from the rigor cycle.

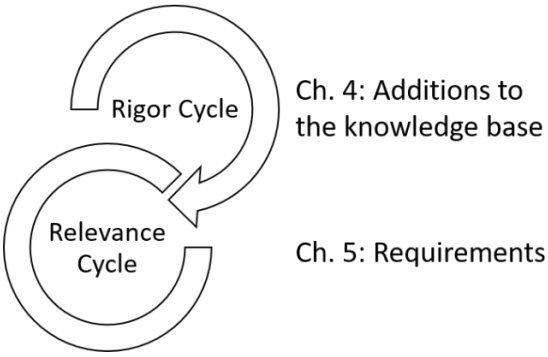


Figure 5-1: The stage in the research in which requirements are defined

'Build' and 'evaluate' are important issues in design science (March & Smith, 1995). 'Build' refers to the development of constructs, models, methods and artefacts, whereas 'evaluate' refers to the development of criteria and the assessment of the output's performance against those criteria (Osterwalder, 2004). Osterwalder (2004) interprets this by suggesting that constructs, models, methods and artefacts are built to perform a specific task and then become the object of study, which must be evaluated. A *proposition* is a declarative statement of a concept (Avan & White, 2001) which in this research is used to develop a model of the AMDI. In effect, the model is the result of a set of propositions which outline the elements and their relationships. Section 5.5 describes the design propositions used in this research to develop the AMDI model in Chapter 6 which is evaluated in the test cases in Chapter 7. Building on the foundation provided by the propositions, *design principles* are further defined at a more detailed level to provide scope and direction for the design. Design principles can be defined as "normative, reusable and directive guidelines, formulated towards taking action by the information system architects" (Bharosa & Janssen, 2015 p. 472). Section 5.6 describes the design principles used in this research to develop the AMDI

model. Figure 5-2 below shows the relationship between the requirements, the propositions and the principles.

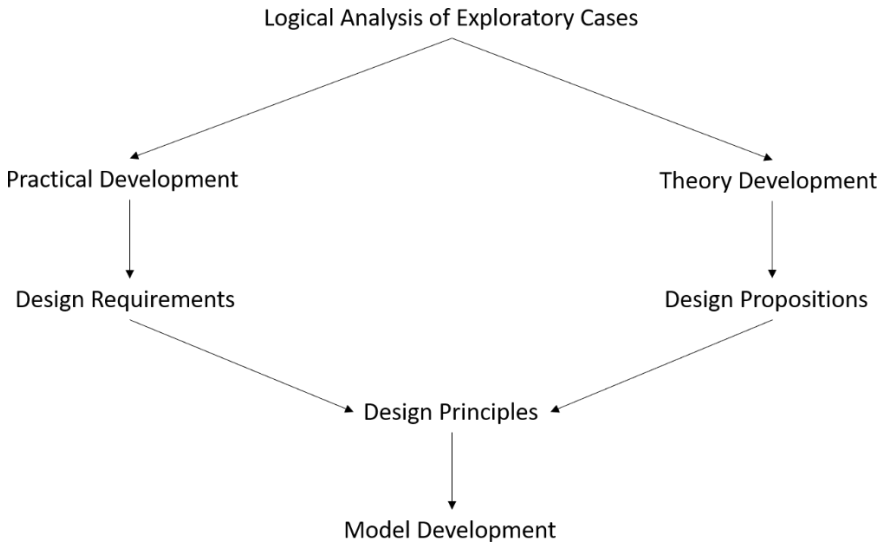


Figure 5-2: The relationship between the requirements, propositions and principles

Figure 5-2 above shows that the requirements and propositions are essentially the result of the exploratory case study analysis. The requirements define the practical side of the design whereas the propositions move the theory development forward. The design principles are based on the requirements and the propositions and provide a detailed scope and direction for the model build. The design and implementation of effective data management policies need to be informed by a holistic understanding of the system components, their complex interactions, and how they respond to various changes. The model of AMDIs integrates different elements into a unified framework. Because there are many different model types, section 5.5 discusses and describes the modelling approach used in this research, and the modelling choices that affect the model design which provides a partial answer to Research Question 4. Figure 5-3 below shows how this Chapter has been structured and the design approach used.

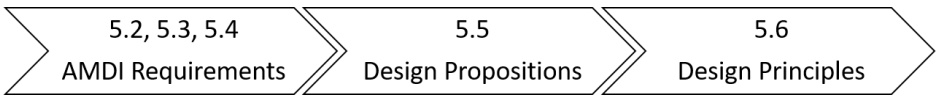


Figure 5-3: Structure of Chapter 5.

Chapter 5 begins by outlining the model requirements as identified in the literature review and the exploratory case studies. Motivated by the requirements, this Chapter then identifies design propositions and design principles which provide input for the AMDI which is described in Chapter 6. Chapter 5 concludes by describing the modelling approach adopted by this research providing the background for the AMDI model.

## 5.2 Requirements of the AMDI Model

According to (Davis, 2005, p. 3), a requirement is an "externally observable characteristic of a desired system". Buede (2009) believes that requirements are at the foundation of the systems engineering process. For example, requirements "enable the engineers of systems to partition the design problem into components that can be worked in parallel while maintaining design control" (Buede, 2009 p. 151). Because we can focus on the "generally observable characteristics" of the model as being a combination of elements and behaviors we must agree with Buede (2009 p. 151) in that there is value in having a structure for various types of requirements. According to Buede (2009), if the requirements are listed in random order in a requirements document, it is difficult to be sure that a given requirement is not addressed multiple times in that single requirements document. In this research we therefore follow Davis (2005) and Buede (2009) and cluster the first set of AMDI model requirements according to the "use" of the model in enabling IoT adoption in asset management. In this case, the AMDI fills a particular need. These clusters of requirements are often referred to as either "shareholder requirements" (Buede, 2009) or, more commonly, "*stakeholder requirements*". In this research these types of requirements are referred to as stakeholder requirements. As described in Chapter 1, the primary objective of this research is to develop a model of AMDIs that improves asset management in asset management organizations by accommodating IoT adoption. According to Sokolowski & Banks (2010), the added value of models lie with the communication and conveyance of the fundamental principles and basic functionality of the system which it represents. Therefore, following Sokolowski & Banks (2010), the stakeholder requirements of our model are focused on facilitating communication of IoT system details between stakeholders in an asset management environment and providing a means for collaboration between agents in the asset management organization.

Another type of requirements are often referred to as "system requirements" (Buede, 2009). Following Sokolowski & Banks (2010), the

system requirements identified in this research are focused on enhancing our understanding of the socio-political and technical IoT system requirements in an asset management environment. System requirements generally consist of "component" requirements, and "behavior" requirements (Buede, 2009).

- *Component Requirements*: Requirements indicating necessary components and schema.
- *Behavioral System Requirements*: Requirements indicating desired behavior. In this case the AMDI should perform according to particular patterns.

Section 5.3 deals with requirements related to IoT usage in asset management (stakeholder requirements). Sections 5.4 and 5.5 deal with requirements related to the system (components, schema and environment) of AMDI's. Section 5.6 deals with behavioral requirements related to behaviors of AMDIs. The requirements are tested in Chapter 7 according to the test criteria defined in Chapter 2 section 2.4.5.

## 5.3 Stakeholder Requirements Facilitating Communication

The results of the exploratory case studies suggest that enabling effective knowledge management, sharing and collaboration between domains and divisions at all levels of the organization as well as between government and citizens is essential to enabling IoT adoption in asset management organizations. Traditionally this knowledge sharing is based on historical data in which past performance of systems can be analyzed in order to identify lessons learned. Documenting the knowledge gained is essential to facilitating communication of the IoT system. For example, RWS staff suggested that documentation of the LMW and WIM systems was invaluable in communicating requirements during tender processes. This leads us to the first stakeholder requirement which reads as follows: *1. The AMDI model should provide a method to document the IoT system for future reference*.

The exploratory case studies back up suggestions made by (Chen & Jin, 2012) that collecting information accurately and in real time allows managers to exploit resources reasonably, reduce production costs, improve the ecological environment, and improve products. In business process decomposition, the decomposition and decentralization of existing business processes increases implies not only real-world data flows to the business processes so that they can optimize their execution, but also the capability to delegate functionality to devices. This may allow for more

system flexibility in which the system is better able to react to dynamic changes (Spiess, & Karnouskos, 2007). As such, it is important to identify system specifications such as functionality requirements of delegated functionalities. For example, the sensing of water levels and the transmission of these values to a storage facility via the internet. This leads us to our second stakeholder requirement which reads as follows: *2. The AMDI model should provide a point of reference for designers to extract system specifications for IoT adoption in asset management organizations.*

Making information available to the public greatly improves government transparency (Castro, 2008b). Increased openness and transparency helps ensure proper oversight and reduces government waste. For example, making ground water levels openly accessible in Rotterdam allows insight into the effects of local maintenance on water levels which may affect housing foundations. Public accessibility requires ensuring interoperability, suggesting that IoT systems be loosely coupled, a design in which each of the system components have little or no knowledge of the definitions of the other separate components. For example, with the coupling of classes, interfaces, data, and services. This allows the extensibility of the model meaning that appropriate ontologies may be linked to the AMDI. This leads us to our third stakeholder requirement which reads as follows*: 3. The AMDI model should be loosely coupled, following the principles of linked open data.*

As discussed in the exploratory case studies, facilitating communication of the IoT system configuration can improve service optimization through self-organization. For example, when real-time IoT information is made available, service providers operating in the Rotterdam Municipality are able to take the initiative in providing measures to guard against damage caused by rising or falling ground water levels. Self-organizing systems that optimize themselves with regard to resource availability and consumption may enable optimization according to usage and de-centralized long-term support (Sadeghi et al., 2015). This leads us to our fourth stakeholder requirement which reads as follows: *4. The AMDI model should be easily shared.*

Due to increasing stresses on budgets and personnel as well as increased utilization of public utility infrastructure, public AM organizations increasingly need to intelligently manage their infrastructure with fewer resources (Rathore et al., 2016). Facilitating communication of IoT systems may bring an improved understanding of complex processes which is expected to help improve the efficiency of management and infrastructure services (Kothari et al., 2015). The

exploratory case studies all demonstrate that IoT systems generally have large amounts of interfaces and that data needs to be shared between multiple applications in various formats. As such, there are often a number of agents who are required to work on various parts of IoT system. Adopting an easily recognizable way of working is therefore essential for facilitating communication of the system configuration. This leads us to our fifth stakeholder requirement which reads as follows: *5. The AMDI model should adhere to conceptual modelling best practices.*

Operational barriers to IoT adoption in asset management include technical issues such as limitations in information technology (IT) infrastructural capabilities (Zeng et al., 2011). According to Scarfo (2014), the main technological challenges include architecture, energy efficiency, security, protocols and quality of service. An important enabler for the IoT is to permit others to access and use the things that have been published publicly on the internet. For example, the LMW network of RWS makes use of a multitude of different technologies and protocols. Overcoming these issues is critical to being able to leverage IoT to improve asset management. This leads us to our sixth stakeholder requirement which reads as follows: *6. The AMDI model should be interoperable.*

Table 5-1 below summarizes the stakeholder requirements facilitating communication of IoT system details between stakeholders in an asset management organization.

Table 5-1: Stakeholder requirements facilitating communication of IoT system details between stakeholders in an asset management organization

| **Requirement** | **Literature** |
|---|---|
| 1. The AMDI model should provide a method to document the IoT system for future reference | (Chen & Jin, 2012) |
| 2. The AMDI model should provide a point of reference for designers to extract system specifications for IoT adoption in asset management organizations | (Spiess, & Karnouskos, 2007) |
| 3. The AMDI model should be loosely coupled, following the principles of linked open data | (Castro, 2008b) |
| 4. The AMDI model should be easily shared | (Sadeghi et al., 2015) |
| 5. The AMDI model should adhere to conceptual modelling best practices | (Kothari et al., 2015) |
| 6. The AMDI model should be interoperable | (Zeng et al., 2011) |

## 5.4 Component Requirements Enhancing Understanding

The following sections outline the component requirements which improve understanding of AM though IoT.

### 5.4.1 Component Requirements: Component Implementation

The component requirements for dealing with component implementation can be focused on types of components used by IoT. Requirements regarding implementation of data, technology and agents will be discussed in this section.

*Data*

Data has long been recognized as a core component of information systems and has been generally defined as the measure or description of objects or events (Checkland & Holwell, 1997; Kettinger & Li, 2010). The term "data" is often used in everyday terminology to refer to either raw data or to information (Khatri & Brown, 2010; Lin et al., 2007; Wende & Otto, 2007). In fact there is an important difference between the two (Kettinger & Li, 2010). The term, "data" is often distinguished from "information" by referring to data as raw data, and referring to information as data put in a context or data that has been processed (Huang et al., 1999; Price & Shanks, 2005). Perhaps the largest disrupting factor of IoT adoption lies in the fact that data is being created faster, in greater quantities and with greater levels of variation as we see in all the cases. Data is provided real time to systems and people so that information becomes instantly available and can be quickly acted upon. This leads us to our seventh requirement which reads as follows: *7. Provides means to describe IoT data included in the AMDI.*

For information to be gained from all this data, context is required. This contextual data is gained from data which describes the data that is being created, often referred to as "metadata". Often, metadata also provides data about the sensor itself or about the object or thing that is being sensed. Metadata is often defined as data about data (Bargmeyer & Gillman, 2000; Khatri & Brown, 2010). As such we must also recognize that metadata is also data. According to Khatri & Brown (2010), metadata describes what the data is about and provides a mechanism for a concise and consistent description of the representation of data, thereby helping interpret the meaning or "semantics" of data. According to Khatri & Brown

(2010), physical metadata includes information about the physical storage of data; domain-independent metadata includes descriptions such as the creation or modification of data and the authorization, audit and lineage information related to the data; and user metadata includes annotations that users may associate with data items or collections. The cases show that metadata is proven to be an important factor in data sharing as re-use becomes only possible if the user is aware of the characteristics of the data provided. This leads us to our eighth component requirement which reads as follows: *8. Provides means to describe all forms of metadata of IoT data in the AMDI.*

*Technology*

Technology within data infrastructures is required to manage connected data resources. This technology must support the data management process (Thomas et al., 1994). The general problem of retrieval faced by the data analysts is that a vast quantity of data is available, but the nature, quality, structure, type, and precise location are often not known (Nebert, 2004; Roberts et al., 2006; Thomas et al., 1994). Furthermore, development issues incurred by legacy and heterogeneous systems drive the need for interoperability. According to Yue et al. (2015) the core of IoT lies with the sharing of information between things and things or between people and things. Yue et al. (2015) summarize the basic characteristics of things as comprehensive perception, reliable transmission and intelligent processing. Comprehensive perception includes the acquisition of observations or measurements by using perception, acquisition and measurement technology such as RFID, two-dimensional code and sensors, etc. Reliable transmission includes ensuring that the objects have access to information networks and can realize reliable information interaction and sharing through communications networks. Intelligent processing is the analysis of sensor data by using a variety of intelligent computing technology, to achieve intelligent decision-making and control (Yue et al., 2015). For example, the RWS LMW case demonstrates that critical infrastructure such as the Maeslantkering storm surge barrier can only be possible if the technological infrastructure can be relied upon. This leads us to our ninth component requirement which reads as follows: *9. Provides means to describe the technical infrastructure which enables the AMDI.*

AMDIs are increasingly being migrated to cloud solutions whereby service providers provide the hard and software necessary to manage the data resources (Vaquero et al., 2008). According to Vaquero et al. (2008), infrastructure providers manage a large set of computing resources, such

as storing and processing capacity and are able to split, assign and dynamically resize these resources to build ad-hoc systems as demanded by customers. This is commonly known as the Infrastructure as a Service (IaaS) scenario (Mell & Grance, 2011). Cloud systems can also provide the software platform where systems run on. This is known as Platform as a Service (PaaS) (Mell & Grance, 2011; Vaquero et al., 2008). Finally, there are services which run applications. An example of this is the online alternatives of typical office applications such as word processors. This scenario is often called Software as a Service (SaaS) (Mell & Grance, 2011; Vaquero et al., 2008). As such, data can only be turned into information on an application platform, be it a spreadsheet or a specifically designed mobile "app". An example taken form the case studies can be seen in the "zwemwater.nl" app. This leads us to our tenth component requirement which reads as follows: *10. Provides means to describe the application landscape which enables the AMDI.*

*Agents*

In a CAS, multiple agents often interact with one another in large variety of ways. Agents are entities that have the ability to intervene meaningfully in the course of events (Choi et al., 2001). Data infrastructures include people as agents. People are seen as a key element in data infrastructures as people are responsible for the decision making, design, implementation, and use of the data infrastructure (Anderies et al., 2004; Grus et al., 2010; Rajabifard et al., 2002). With regards to people, knowledge management is of utmost importance (Ure et al., 2009). Local knowledge is often central to the ongoing maintenance of data, particularly in the face of unanticipated and unpredictable changes in local context and practice (Ure et al., 2009) as people have a direct influence on the role of organizational culture within data infrastructures, and effective data infrastructures are developed and applied around commonly felt needs (de Man, 2006). The cases demonstrate the complexity of the agency formed in different organizations. This means that there can be no "one-size-fits-all" model, but that implementations should be tailored to meet specific needs. This leads us to our eleventh component requirement which reads as follows: *11. Provides means to describe the human and organizational agents driving the AMDI.*

Significantly, artificial intelligence is becoming more and more prevalent in service oriented environments, especially in the form of software commonly known as "bots' (Gianvecchio et al., 2011). As such, artificial intelligence and robotics as agents are beginning to play an important role in the development of data infrastructures as more and

more infrastructure management processes become automated. Agents have varying degrees of connectivity with other agents, through which information and resources can flow. They possess schema that determine the states and rules of their behavior (Choi et al., 2001) as seen in the automation of storm surge barriers and pumping stations based on rules driven by the data. This leads us to our twelfth component requirement which reads as follows: 12*. Provides means to describe the technological agents driving the AMDI.*

*Summary*
Table 5-2 below summarizes the component requirements dealing with component implementation of IoT.

Table 5-2: Component requirements dealing with component implementation of IoT

| **Requirement** | **Source** |
|---|---|
| 7. Provides means to describe all forms of IoT data included in the AMDI | (Huang et al., 1999) |
| 8. Provides means to describe all forms of metadata of IoT data in the AMDI | (Khatri & Brown, 2010) |
| 9. Provides means to describe the technical infrastructure which enables the AMDI | (Yue et al., 2015) |
| 10. Provides means to describe the application landscape which enables the AMDI | (Vaquero et al., 2008) |
| 11. Provides means to describe the human and organizational agents driving the AMDI | (Choi et al., 2001) |
| 12. Provides means to describe the technological agents driving the AMDI | (Gianvecchio et al., 2011) |

### 5.4.2 Component Requirements: Data Governance Implementation

The component requirements for dealing with component implementation can be focused on types of components used by IoT. Requirements regarding implementation of organizational capability, alignment, clarification and compliance will be discussed in this section.

*Organizational Capability*
Many researchers agree that data governance has an organizational dimension (Khatri & Brown, 2010; Otto, 2013; Wende & Otto, 2007). For example, Wende & Otto (2007) believe that data governance specifies the

framework for decision rights and accountabilities to encourage desirable behavior in the use of data. Decision-making bodies need to be identified for each organization, and data governance must be institutionalized through a formal organizational structure that fits with a specific organization (Malik, 2013). Decision rights indicate who arbitrates and who makes those decisions (Dyché, 2007). According to Dawes (2010), "stewardship" focuses on assuring accuracy, validity, security, management, and preservation of information holdings. For example, in the RWS LMW case, the ownership of the data lies with the Water Management Division, whilst Stewardship of the data and the system is delegated to the Central Information Division. As such the Water Management Division is responsible for defining the requirements of the data, and the Central Information Division is responsible for ensuring these requirements are met. This leads us to our thirteenth component requirement which reads as follows: *13. Provides means to describe the ownership and stewardship of data within the AMDI (including decision rights), whilst balancing the roles of agents, separating duties and concern of agents within the AMDI.*

Malik (2013) indicates the need to establish clear communications and patterns that would aid in handling policies for quick resolution of issues, and Thompson et al. (2015) show that coordination of decision making in data governance structures may be seen as a hierarchical arrangement in which superiors delegate and communicate their wishes to their subordinates, who in turn delegate their control. The RWS case demonstrated a clearly defined contract type coordination approach, but all the cases leant strongly on self-organization and mutual adjustment through standardization. This leads us to our fourteenth component requirement which reads as follows: *14. Provides means to improve coordination of decision making with regards to data management.*

*Alignment*

Data governance should ensure that data meets the needs of the business (Panian, 2010). A data governance program must be able to demonstrate business value, or it may not get the executive sponsorship and funding it needs to move forward (Smallwood, 2014). Describing the business uses of data establishes the extent to which specific policies are appropriate for data management. According to Panian (2010), if used correctly, data can be a reusable infrastructure as data is a virtual representation of an organization's activities and transactions and its outcomes and results. The cases showed that most of the data requirements were defined in the component requirements provided in

the technical documentation. However, it was clear that this was often a missing factor and attention was drawn to this by a number of interviewees in the cases. This leads us to our fifteenth component requirement which reads as follows: *15. Provides means to align business data needs with data capabilities provided by the AMDI, including the definition of data quality requirements.*

Data governance also provides the framework for addressing complex issues such as improving data quality or developing a single view of the customer at an enterprise level (Panian, 2010). Wende & Otto (2007) believe that a data quality strategy is therefore required to ensure that data management activities are in line with the overall business strategy. The strategy should include the strategic objectives which are pursued by data quality management and how it is aligned with the company's strategic business goals and overall component scope. Data quality is considered by many researchers to be an important metric for the performance of data governance (Khatri & Brown, 2010; Otto, 2011b; Wende & Otto, 2007). All the cases showed evidence of a specific data strategy which needed to followed. Although not necessarily called such, the documentation provided direction within specific documents as to the data strategy to be followed. This leads us to our sixteenth component requirement which reads as follows: *16. Provides means to include processes to develop a data strategy, including effective policies and procedures with regards to data management.*

*Clarification*

Attention to business areas and enterprise entities should be the responsibility of the appropriate data stewards who will have the entity-level knowledge necessary for development of the entities under their stewardship (Smith, 2007). To ensure that the data is interpretable, metadata should be standardized to provide the ability to effectively use and track information (Khatri & Brown, 2010). This leads us to our seventeenth component requirement which reads as follows: *17. Provides means to develop a shared data commons, including standards.*

Data governance principles therefore reflect and preserve the value to society from the sharing and analysis of anonymized datasets as a collective resource (Al-Khouri, 2012). Coordination manages dependencies between activities (Malone & Crowston, 1990). These dependencies arise from the mutual use of common objects to carry out a task (Malone & Crowston, 1990). Thus, communication is necessary for coordinating processes. This leads us to our eighteenth component requirement which reads as follows: *18. Provides means to standardize*

*operational processes and facilitate communication regarding data activities.*

*Compliance*

Mechanisms need to be established to ensure organizations are held accountable for these obligations through a combination of incentives and penalties (Al-Khouri, 2012) as, according to Felici et al. (2013), governance is the process by which accountability is implemented. In such a manner, accountability can unlock further potential by addressing relevant problems of data stewardship and data protection in emerging in data ecosystems. This leads us to our nineteenth component requirement which reads as follows: *19. Provides means to define accountability with regards to data management and data use.*

According to Malik (2013), determination of policies for governance is typically done in a collaborative manner with IT and business teams coming together to agree on a framework of policies which are applicable across the whole organization. Tallon (2013) regards data governance practices as having a social and, in some cases, legal responsibility to safeguard personal data through processes such as "privacy by design", whilst Power & Trope (2006) suggest that risks and threats to data and privacy require diligent attention from organizations to prevent "bad things happening to good companies and good personnel" (Power & Trope, 2006, p. 471). This leads us to our twentieth component requirement which reads as follows: *20. Provides means to enforce policies regarding data management and data use, including ensuring data privacy and data security.*

*Summary*

Table 5-3 below summarizes the component requirements dealing with Data Governance of IoT data.

Table 5-3: Requirements dealing with Data Governance of IoT data.

| **Requirement** | **Source** |
|---|---|
| 13. Provides means to describe the ownership and stewardship of data within the AMDI (including decision rights), whilst balancing the roles of agents, separating duties and concern of agents within the AMDI | (Wende & Otto, 2007) |
| 14. Provides means to improve coordination of decision making with regards to data management | (Malik, 2013) |

| Requirement | Source |
|---|---|
| 15. Provides means to align business data needs with data capabilities provided by the AMDI, including the definition of data quality requirements | (Panian, 2010) |
| 16. Provides means to include processes to develop a data strategy, including effective policies and procedures with regards to data management | (Panian, 2010) |
| 17. Provides means to develop a shared data commons, including standards | (Khatri & Brown, 2010) |
| 18. Provides means to standardize operational processes and facilitate communication regarding data activities | (Al-Khouri, 2012) |
| 19. Provides means to define accountability with regards to data management and data use | (Felici et al., 2013) |
| 20. Provides means to enforce policies regarding data management and data use, including ensuring data privacy and data security | (Malik, 2013) |

### 5.4.3 Component Requirements: Environmental Effects on AMDIs

A data infrastructure, as CAS, both reacts to and creates the environment it is operating in (Brous et al., 2014; Choi et al., 2001). In this way, a data infrastructure is inseparable from its environment. The component requirements for dealing with managing environmental effects on AMDIs can be focused on types of environments in which IoT is implemented. Requirements regarding the physical environment, the cultural environment, and the political environment will be discussed in this section.

*Physical*

With regards to AMDIs, there is no separation between a system and its environment and change should be seen in terms of co-evolution with regards to all the related elements within the system (Chan, 2001). This leads us to our twenty-first component requirement which reads as follows: *21. Provides means to describe the physical environment within which the AMDI is located.*

Because one should not separate the AMDI from its environment, it is difficult to attribute success or failure to a particular factor and tracking cause-and-effect relationships is hard. All data infrastructures are unique in character and behavior. This makes it difficult to standardize data infrastructure implementation (Grus et al., 2010). This leads us to

our twenty-second component requirement which reads as follows*: 22. Provides means to describe how the physical environment affects the AMDI.*

*Cultural*

The physical environment forces changes in the CAS, which in turn induces changes in the physical environment. (Choi et al., 2001) explain this phenomenon with the example of a team. As team members grow more cohesive, they collectively become more distant from the outside environment, and vice versa. This leads us to our twenty-third component requirement which reads as follows: 23*. Provides means to describe the cultural environment within which the AMDI is located.*

Such interdependencies ensure environments are very dynamic requiring systems to adapt and evolve to ensure fitness to their environment. This leads us to our twenty-fourth component requirement which reads as follows: *24. Provides means to describe how the cultural environment affects the AMDI.*

*Political*

According to Thompson et al. (2015), technical solutions are often implemented without consideration for the wider governance framework. This leads us to our twenty-fifth component requirement which reads as follows: *25. Provides means to describe the political environment within which the AMDI is located.*

Thompson et al. (2015) believe that a successful solution should be fitted to the unique organizational context. The cases support Weber et al. (2009) and Thompson et al. (2015) in that there can be no "one-size fits-all" in this regard. This leads us to our twenty-sixth component requirement which reads as follows: *26. Provides means to describe how the political environment affects the AMDI.*

*Summary*

Table 5-4 below summarizes the component requirements dealing with managing environmental effects on AMDIs.

Table 5-4: Requirements dealing with managing environmental effects on AMDIs

| Requirement | Source |
|---|---|
| 21. Provides means to describe the physical environment within which the AMDI is located | (Chan, 2001) |
| 22. Provides means to describe how the physical environment affects the AMDI | (Grus et al., 2010) |
| 23. Provides means to describe the cultural environment within which the AMDI is located | (Choi et al., 2001) |
| 24. Provides means to describe how the cultural environment affects the AMDI | (Choi et al., 2001) |
| 25. Provides means to describe the political environment within which the AMDI is located | (Thompson et al., 2015) |
| 26. Provides means to describe how the political environment affects the AMDI | (Thompson et al., 2015) |

### 5.4.4 Behavioral Requirements

The requirements for dealing with behaviors of AMDI's can be focused on types of behaviors which AMDIs exhibit. Requirements regarding the dynamism, connectivity, adaptation, and emergence of AMDIs will be discussed in this section.

*Dynamism*
The diversity of skills, experiments, strategies and rules of different agents within a CAS ensures its dynamic adaptive behavior (Rupert et al., 2008). For example, it is difficult for a single agent to evolve and become more useful in an isolated context (Sutherland & van den Heuvel, 2002), so there is a constant exchange of information and needs between the components and the actors in the system (Grus et al., 2010). For example, RWS works with a so called "Domain Team" which is made up of a group of people with a number of different skills, including architecture, business analysis and technical management etc. This leads us to our twenty-seventh requirement which reads as follows: *27. Accommodates dynamism of elements within the AMDI.*

*Connectivity*
The results of the cases suggest that AMDIs should have feedback loop mechanisms (Grus et al., 2010) which enable the system to use its own output to adjust its inputs and processes. For example, RWS and Delfland actively encourage the public to critically review the data provided by their IoT systems and report any discrepancies which may be caused by, for

example in the LMW case, contamination of the sensors, requiring maintenance and reconfiguration. This leads us to our twenty-eighth requirement which reads as follows: *28. Demonstrates connectivity of elements within the AMDI.*

*Adaptation*
AMDIs are able to adjust and adapt themselves to external influences (Cilliers, 2002; Grus et al., 2010; Rotmans & Loorbach, 2009) and an AMDI will change constantly because of the continuous interactions and interdependence between its agents and its environment (Rupert et al., 2008). For example, both Delfland and Rotterdam encourage the active participation of citizens in the management and development of the IoT infrastructure. This has led to a diversity of sensor types, meaning that the networks have had to adapt to be able to accommodate multiple data protocols. This leads us to our twenty-ninth requirement which reads as follows: *29. Accommodates adaptations within the AMDI.*

*Emergence*
As suggested by Merali (2006), macroscopic properties of an AMDI arise from the heterogeneity of its elements and its relevant properties. The system displays a set of properties that is distinct from those displayed by any subset of its elements. For example, in order to gain the full benefit of their systems, asset managers throughout the cases have had to learn to use and trust the data, meaning that, in part, asset managers have themselves needed to become data experts. For example, at Rotterdam, instruments to model the flow of rain water across the street and to portray the possible effects of measures are being developed. The calculations also describe environmental performance in each area, or how large the theoretical waste emission from the mixed sewage system is on surface water. This leads us to our thirtieth requirement which reads as follows: *30. Accommodates emergence of behaviors within the AMDI.*

*Summary*
Table 5-5 below summarizes the behavioral requirements dealing with managing environmental effects on AMDIs.

Table 5-5: Behavioral requirements for dealing with behavioral effects on AMDI's

| Requirement | Source |
|---|---|
| 27. Accommodates dynamism of elements within the AMDI | (Rupert et al., 2008) |
| 28. Demonstrates connectivity of elements within the AMDI | (Grus et al., 2010) |
| 29. Accommodates adaptations within the AMDI | (Rotmans & Loorbach, 2009) |
| 30. Accommodates emergence of behaviors within the AMDI | (Hanseth & Lyytinen, 2010) |

On the basis of these requirements, section 5.5 defines the design propositions used to guide the research and the design of the model in Chapter 6.

## 5.5 Design Propositions

Having defined the requirements which need to be met by the AMDI model, in this section we generate propositions for the design of the AMDI model. The views used to describe the exploratory case studies not only provide us with requirements of the AMDI model, but also with design propositions. We acknowledge that CAS theory demands a complex interaction between elements, however, for analytical purposes we choose to "freeze" the elements and view each element as separate variables. According to Denyer, Tranfield, & Aken (2008), design propositions are "templates" which can be used to develop solutions for a class of problems. As such, design propositions, whilst not offering complete solutions, do offer input for the design of particular solution (Denyer et al., 2008). In order to develop the design propositions, we analyzed the requirements as read in section 5.4 taking in to consideration the views of the exploratory case studies. The requirements are drawn from the literature review in Chapter 3 and the case study analysis in Chapter 4. As seen in Figure 5-4 below, we conclude that three key functional elements may improve asset management and facilitate IoT adoption in AMDIs, namely "Components", "Data Governance" and the "Environments". The functional elements are proposed based on the criteria that:

- The functional elements cover as many of the requirements as possible

- The functional elements are accepted due to already existing research. For our purposes we included research in domains other than asset management.

With respect to the views describing the exploratory case studies, we group the different elements of AMDIs into the main functional element, "Components" which occur within "Environments" and we view "Data Governance" as the schema which directs these constructs.

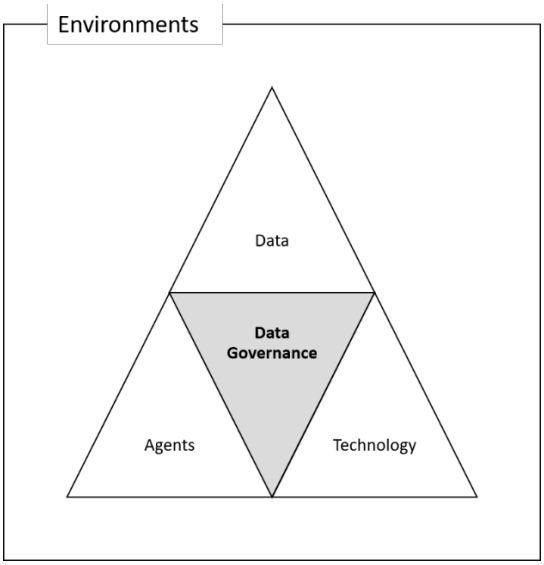


Figure 5-4: Functional elements of IoT AMDIs

The propositions are described according to the potential impact the functional elements (as exposed in the answers to research questions 2 and 3) may have on the improvement of understanding of asset management through IoT as discussed in response to research question 1, namely, *performance analysis*, *expectation management*, and *infrastructure service processes*. Figure 5-5 below demonstrates how the functional elements relate to the expected improvements to asset management due to potential structural changes to the AMDI as identified in of the exploratory case studies. The elements of AMDIs (component, data governance and environments) as described in views 2 and 3 of the exploratory case studies introduce changes to the organization, as suggested by the duality of IoT (Orlikowski, 1992), which result in improvements to understanding of asset management through IoT as described in view 1 of the exploratory case studies.

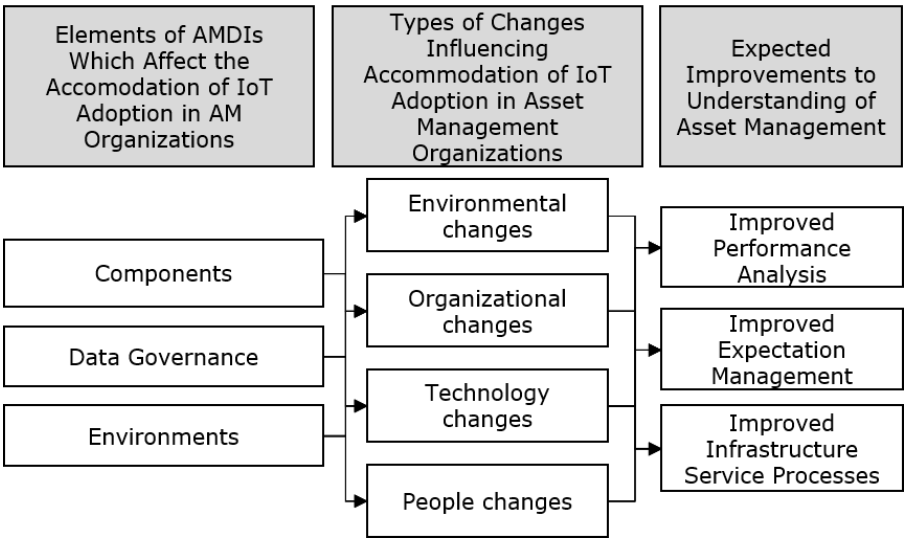


Figure 5-5: The relationship between elements and expected improvements to asset management.

The following sections discuss the propositions which deal with the relationship between the functional elements of the IoT enabled AMDI and its uses as described in Figure 5-5 above, linking these elements with the value of modelling AMDIs improve understanding of asset management though IoT.

### 5.5.1 Functional Element – Components

AMDIs consist of relatively stable and simple components (Grus et al., 2010; Haghnevis & Askin, 2012; Rupert et al., 2008; Sutherland & van den Heuvel, 2002) which are the constituent parts of the system. The overall behavior of an AMDI emerges from the activities of lower-level components although, typically, an AMDI will die when an essential component is removed (Miller & Page, 2009). Brous et al. (2014) have identified three essential components of data infrastructures, namely data, agents and technology. Technology can also be further separated into hardware, the collection of physical components that constitute an information system, and software, that part of an information system that consists of computable instructions. People and, increasingly, technology are impacting the data infrastructure through agency. An agent is something or somebody that "can be viewed as perceiving its environment through sensors, and acting upon that environment through actuators"

(Gong, 2012, p. 75). This brings us to our first design proposition which reads as follows:

**Design Proposition 1:** Configuring the elements of AMDIs to accommodate IoT adoption improves understanding of asset management through IoT.

The first component of AMDIs is *data*, which has long been recognized as a core factor in information systems and has been generally defined as the measure or description of objects or events (Checkland & Holwell, 1997; Kettinger & Li, 2010). Data infrastructures necessarily include data. The term "data" is often used in everyday terminology to refer to either raw data or to information. In fact there is an important difference between the two (Kettinger & Li, 2010). Data are facts about objects, subjects or events within or without the organization. These facts generally involve the condition of the object or subject or refer to a transaction involving that object or subject. Data only becomes information once it is given context and presented in a form that people are able to understand. For example, although it is clear that a great deal of data is being produced, managed and maintained, asset managers within Water Authority Delfland observed that they often do not receive the data that they require because the data is produced by (sub)contractors who produce only the data that they themselves require. Also, data that is produced is often "locked" into systems as, for example, logging files. Retrieving the data for objectives other than those originally defined can be difficult and time consuming. Also, at Rijkswaterstaat, data is produced in order to achieve certain goals. It very much depends on the goals of the parties producing the data as to which data is being produced and how.

The second component*, technology* within data infrastructures is required to manage connected data resources. This technology must support the data process (Thomas et al., 1994). The general problem of retrieval faced by the data analysts is that a vast quantity of data is available, but the nature, quality, structure, type, and precise location are often not known (Nebert, 2004; Roberts et al., 2006; Thomas et al., 1994). Furthermore, development issues incurred by legacy and heterogeneous systems drive the need for interoperability. Rijkswaterstaat has a well-developed data access network which allows access to users based on open standards. Although it creates and manages its metadata locally, Rijkswaterstaat also makes use of external facilities to publish its data. For example, Rijkswaterstaat uses the

National Spatial Data metadata library, National Geo-Register (NGR) to publish and find its spatial data. Other data types are generally stored in specialized systems such as digital libraries for images and digital photography. The metadata for these data types is created, stored and searched within the system itself.

A third component of AMDI are the *agents*. Agents are seen as a key element (Anderies et al., 2004; Grus et al., 2010; Rajabifard et al., 2002) in AMDIs as agents are responsible for the decision making, design, implementation, and use of the data infrastructure. Without agents, the AMDI would have no function, nor would it evolve. Knowledge management is of utmost importance for agency (Ure et al., 2009). Local knowledge is often central to the ongoing maintenance of data, particularly in the face of unanticipated and unpredictable changes in local context and practice (Ure et al., 2009). Furthermore, people have a direct influence on the role of organizational culture within data infrastructures (de Man, 2006). de Man (2006) believes that effective data infrastructures are developed and applied around commonly felt needs. For example, Rijkswaterstaat employees appear to be the driving force behind the success of their AMDI. Despite major reorganizations over the last few years and large budget cuts, Rijkswaterstaat has a culture of "getting things done". Workarounds and quick fixes are often made at a local level in order to ensure that the system continues to function. This shows that local knowledge is central to the ongoing maintenance of data within the Rijkswaterstaat.

### 5.5.2 Functional Element – Data Governance

Data governance is about coordinating data management - identifying the fundamental decisions regarding data that need to be made and who should be making them. Coordination is a process in which agents engage in order to ensure a community of individual agents act in a coherent manner (Hyacinth S. Nwana, 1996). The restricted availability of resources in asset management data infrastructures can cause conflict and this conflict demands coordination. In a world where resources for data management are constantly under review and limitations are a matter of course, competing for resources may be a major driver for the adoption of IoT in infrastructure management, but may also contain challenges. This leads us to our second main design proposition which reads as follows:

**Design Proposition 2:** Implementing data governance improves understanding of asset management through IoT.

The organization of data governance should not be seen as a "one size fits all" approach (Wende & Otto, 2007). Instead, decision-making bodies need to be identified for each individual organization, and data governance must be institutionalized through a formal organizational structure that fits with a specific organization (Malik, 2013). Decision rights indicate who arbitrates and who makes those decisions (Dyché, 2007). According to Dawes (2010), "stewardship" focuses on assuring accuracy, validity, security, management, and preservation of information holdings. As such we have observed that all three case studies utilized differing forms of organization and placed ownership and stewardship in different places. For example, RWS was very specific in stating that ownership of the data lay with the Water Management Division of RWS, whilst stewardship of the data and the systems lay with the Central Information Division. Rotterdam Municipality on the other hand placed ownership and stewardship together in one single department.

Data governance should ensure that data meets the needs of the business (Panian, 2010) and data governance programs must be able to demonstrate business value (Smallwood, 2014). Describing the business uses of data establishes the extent to which specific policies are appropriate for data management. According to Panian (2010), if used correctly, data can be a reusable infrastructure as data is a virtual representation of an organization's activities and transactions and its outcomes and results. As such, data governance should ensure that data is "useful" (Dawes, 2010). According to Dawes (2010), information should be helpful to its intended users, or should support the usefulness of other disseminated information. For example, the sensor data collected by the Water Authority Delfland is directly used by the pumping stations to automate water level management and the data collected by the LMW system at RWS is used for a multitude of uses, including water management and automating storm surge barrier processes.

According to Smith (2007), governing data appropriately is only possible if it is properly understood what the data to be managed means, and why it is important to the organization. Data understanding is essential to any application development, data warehousing or services-oriented-architecture effort and misunderstood data or incomplete data requirements can affect the successful outcome of any asset management project (Smith, 2007). Smith (2007) believes that the best way to avoid problems created by misunderstanding the data, is to create an enterprise data model (EDM) and that creating and developing an EDM should be one of the basic activities of data governance. For example, RWS has done

much work to develop a set of core-registrations which make up the enterprise data model. However, all three case studies identified a lack of clarity with regards to the total data landscape as being a debilitating factor with regards to system development.

Data governance includes a clearly defined authority to create and enforce data policies and procedures (Wilbanks & Lehman, 2012). Panian (2010) states that establishing and enforcing policies and processes around the management data is the foundation of an effective data governance practice. Delineating the business uses of data establishes the extent to which data is an enterprise wide infrastructure, and thus what specific policies are appropriate (Khatri & Brown, 2010). Mechanisms need to be established to ensure organizations are held accountable for these obligations through a combination of incentives and penalties as governance is the process by which accountability is implemented. For example, sensors which are placed or owned on private property may by subject to rules and regulations regarding privacy set out by the General Data Protection Regulation (GDPR).

### 5.5.3 Functional Element – Environments

A third element in the AMDI is the *environment*. An AMDI, as CAS, both reacts to and creates the *environment* it is operating in (Brous et al., 2014; Choi et al., 2001). In this way, an AMDI is inseparable from its environment and dynamic, emergent realities are created through interaction. As suggested by Orlikowski (1992) the environment forces changes in the AMDI, which in turn induces changes in the environment. For example, the LMW measurement network was originally three separate networks. The insights provided by the three separate systems demonstrated the need to manage the national water ways in a holistic way and the necessity to have a national view of the water systems, causing the three measuring networks to be integrated into one network. When people or things act (or react) on an environment, that environment can be changed in unexpected ways (Brous & Janssen, 2015a). This brings us to our third design proposition which reads as follows:

**Design Proposition 3:** Configuring AMDIs to accommodate cultural, physical and political environments improves understanding of asset management through IoT.

When internal or external actors act, the environment in which data infrastructures exist may change often and quickly, forcing the data infrastructure to evolve and adapt to these changes. Environmental

characteristics may refer to the sector within which the organization operates, or may represent cultural, political or physical conditions (Wejnert, 2002). In our AMDI model, we include three relevant environmental factors of cultural, physical and political environments within the asset management sector.

## 5.6 Design Principles

Section 5.5 provided the design propositions. These propositions help describe design assumptions on a high level of abstraction and are used to identify specific principles for the design of the AMDI model. This section provides detailed principles that are used for the design of the AMDI model. Van Bommel et al. (2006) argue that steering the overall enterprise development within a large organization requires constraining the design space through the definition of principles. According to the TOGAF architecture framework, "Principles are general rules and guidelines, intended to be enduring and seldom amended, that inform and support the way in which an organization sets about fulfilling its mission" (The Open Group). They are fundamental norms, rules, or values that represent what is desirable and positive for a person, group, organization, or community, and help in determining the rightfulness or wrongfulness of actions. Principles are more basic than policy and objectives, and are meant to govern both. Design principles, in particular, are "normative and directive guidelines" (Bharosa & Janssen, 2015) which aid the architect in the actions that need to be taken.

In the previous sections we describe the practical requirements which were assimilated by analysis of the exploratory case studies, and we propose that understanding and communicating the elements (components, data governance and environments) of AMDIs positively influence understanding of asset management through IoT. In this research we focus on two groups of design principles, namely: 1. principles which facilitate communication of the AMDI design, and 2: principles which enhance our understanding of asset management through IoT.

### 5.6.1 Design Principles Which Facilitate Communication of the AMDI Design

Table 5-5 outlines the design principles as derived from the requirements and the design propositions with regards to facilitating communication of the AMDI design. The principles are observationally derived by analyzing the requirements with regards to the design propositions as seen in table 5-5 below. The principles are numbered. The table shows the relationship of the principles to the requirements and the propositions.

Figure 5-6: Design principles which facilitate communication of the AMDI design.

| Requirements | Propositions | Derived Design Principles |
|---|---|---|
| 1. The AMDI model should provide a method to document the IoT system for future reference | [1-3] with respect to communication | 1. The model is available in widely accepted open formats.<br>2. The model can be edited, stored and recovered for future reference. |
| 2. The AMDI model should provide a point of reference for designers to extract system specifications for IoT adoption in asset management organizations | [1-3] with respect to communication | 3. The model illustrates and simulates the basic components of AMDIs and their interrelationships.<br>4. The model combines object-oriented and agent-oriented perspectives, addressing the socio-technical complexity of infrastructure systems. |
| 3. The AMDI model should be loosely coupled, following the principles of linked open data | [1-3] with respect to communication | 5. The model is extendable where necessary.<br>6. The model includes existing, widely accepted ontologies. |
| 4. The AMDI model should be easily shared | [1-3] with respect to communication | 7. The model uses open, widely accepted modelling schemas and ontology languages. |
| 5. The AMDI model should adhere to conceptual modelling best practices | [1-3] with respect to communication | 8. The model follows W3C modelling specifications. |
| 6. The AMDI model should be interoperable | [1-3] with respect to communication | 9. The model uses open web standards. |

### 5.6.2 Design Principles Which Enhance Our Understanding of AM Through IoT

In this section the principles that guide the design of data governance mechanisms in the AMDI model are described. Table 5-6 below describes the design principles which enhance our understanding of AM through IoT. The data governance principles are numbered, and the numbering continues from the numbering of the component principles.

Table 5-6: Design Principles Which Enhance Our Understanding of AM Through IoT

| Requirements | Propositions | Derived Design Principles |
|---|---|---|
| 7. Provides means to describe all forms of IoT data included in the AMDI | [1] | 10. The model describes metadata and its relationship to IoT related data.<br>11. The model describes IoT related registrations and their relationships. |
| 8. Provides means to describe all forms of metadata of IoT data in the AMDI | [1] | 12. The model describes the different forms of metadata and their relationships to IoT data. |
| 9. Provides means to describe the technical infrastructure which enables the AMDI | [1] | 13. The model describes hardware related to IoT and their relationships.<br>14. The model describes software related to IoT and their relationships. |
| 10. Provides means to describe the application landscape which enables the AMDI | [1] | 15. The model describes required IoT related application components and their relative functions in the architecture. |
| 11. Provides means to describe the human and organizational agents driving the AMDI | [1] | 16. The model describes the roles of people as agents in the AMDI, their relationships and behavior.<br>17. The model describes organizational groups as agents in the AMDI, their relationships and behavior. |
| 12. Provides means to describe the technological agents driving the AMDI | [1] | 18. The model describes bots and robots as technological agents in the AMDI, their relationships and behavior. |
| 13. Provides means to describe the ownership and stewardship of data within the AMDI (including decision rights), whilst balancing the roles of agents, separating | [2] | 19. The model describes the organization of data governance.<br>20. The model describes the loci of data provenance. |

| Requirements | Propositions | Derived Design Principles |
|---|---|---|
| duties and concern of agents within the AMDI | | |
| 14. Provides means to improve coordination of decision making with regards to data management | [2] | 21. The model describes appropriate coordination mechanisms positively associated with IoT adoption. |
| 15. Provides means to align business data needs with data capabilities provided by the AMDI, including the definition of data quality requirements | [2] | 22. The model describes artefacts and relationships which ensure that IoT related data meets the necessary requirements to align with the requirements of the business. |
| 16. Provides means to include processes to develop a data strategy, including effective policies and procedures with regards to data management | [2] | 23. The model includes a data strategy as object, and describes processes to develop and implement the strategy. |
| 17. Provides means to develop a shared data commons, including standards | [2] | 24. The model describes the use of standards to align IoT data and technology with the needs of the asset management organization. |
| 18. Provides means to standardize operational processes and facilitate communication regarding data activities | [2] | 25. The model uses standardized data management frameworks to describe data management activities related to IoT processes. |
| 19. Provides means to define accountability with regards to data management and data use | [2] | 26. The model describes objects which monitor compliancy to norms, policies, laws and regulations |
| 20. Provides means to enforce policies regarding data management and data use, including ensuring data privacy and data security | [2] | 27. The model describes a set of data management artefacts designed to assist business administration and protect company assets. |
| 21. Provides means to describe the physical environment within which the AMDI is located | [3] | 28. A description of the physical environment is an integral part of the AMDI. |
| 22. Provides means to describe how the physical environment affects the AMDI | [3] | 29. The model assimilates potential effects of the physical environment on the AMDI. |

| Requirements | Propositions | Derived Design Principles |
|---|---|---|
| 23. Provides means to describe the cultural environment within which the AMDI is located | [3] | 30. A description of the cultural environment is an integral part of the AMDI. |
| 24. Provides means to describe how the cultural environment affects the AMDI | [3] | 31. The model assimilates potential effects of the cultural environment on the AMDI. |
| 25. Provides means to describe the political environment within which the AMDI is located | [3] | 32. A description of the political environment is an integral part of the AMDI. |
| 26. Provides means to describe how the political environment affects the AMDI | [3] | 33. The model assimilates potential effects of the political environment on the AMDI. |
| 27. Accommodates dynamism of elements within the AMDI | [1-3] with respect to understanding | 34. The model assimilates dynamic change in relationships, behavior and individuals into its design. |
| 28. Demonstrates connectivity of elements within the AMDI | [1-3] with respect to understanding | 35. Every object has a significant relationship with at least one other object in the model. |
| 29. Accommodates adaptations within the AMDI | [1-3] with respect to understanding | 36. The model is configurable and reconfigurable to assimilate specific, local requirements. |
| 30. Accommodates emergence of behaviors within the AMDI | [1-3] with respect to understanding | 37. The model is configurable and reconfigurable to assimilate unforeseen behavioral changes of local agents. |

## 5.7 Conclusion

In this chapter we partially answered Research Question 4 which asks *what does a model of an AMDI that accommodates IoT look like*? We posit that AMDIs are composed of data, technology and agents, and that these components are directed and coordinated by data governance. IoT is used within asset management to improve performance analysis, improve expectation management and improve infrastructure service processes. Modelling the AMDI improves understanding of asset management through IoT by communicating and conveying the fundamental principles and basic functionality of the AMDI, as well as enhancing our understanding of the infrastructure, providing a point of reference for designers to extract system specifications, and providing a means to

document the infrastructure for collaboration efforts and future reference (Sokolowski & Banks, 2010). We began the chapter by defining the requirements of the AMDI model. We identified three types of requirements to which the AMDI model should conform, namely: stakeholder requirements, component requirements and behavior requirements. Stakeholder requirements and component requirements should be seen as more functional requirements, whereas behavioral requirements are considered to be non-functional requirements. After listing and analyzing the requirements, we derived three main propositions: 1. Configuring the elements of AMDIs to accommodate IoT improves understanding of asset management through IoT; 2. Implementing data governance improves understanding of asset management through IoT; and 3. Configuring AMDIs to accommodate cultural, physical and political environments improves understanding of asset management through IoT. Based on the derived propositions we then further derived more specific design principles which drive the model development. The requirements, together with the design propositions and design principles partially answers Research Question 4. The model is described in Chapter 6.

# Chapter 6 The AMDI Model

*"Therefore, good Brutus, be prepared to hear;*
*And since you know you cannot see yourself*
*So well as by reflection, I, your glass,*
*Will moderately discover to yourself*
*That of yourself which you yet know not of."*
**- William Shakespeare (Julius Caesar, Act-I, Scene-II)**

## 6.1 Introduction

In Chapter 5 we described the requirements, principles and propositions which guide and constrain the development of the AMDI model. These requirements, principles and propositions are the result of insights provided by the literature review and exploratory case studies into the duality of IoT adoption and the need to view AMDIs as CAS. For example, the literature review and the exploratory case studies show that IoT can provide asset management with many varied benefits, but can also introduce unexpected risks, forcing unforeseen changes. Based on the requirements, principles and propositions described in Chapter 5, in this Chapter we describe our model of an AMDI which accommodates IoT and which is designed to improve understanding of asset management through IoT. Compliance to the requirements and design principles is made explicit in the summaries in section 6.1.5, section 6.3.4, section 6.4.5 and section 6.5.1. These summaries refer to the level of compliance to the design principles. For compliance to the requirements please refer to sections 5.6.1 and 5.6.2.

Asset managers have struggled over the years to develop IoT systems which produce data they can trust, and asset data is regularly observed to be lacking in quality, to be "noisy" (embedded within significant amounts of meaningless data), or to be missing the required detail (S. Lin, Gao, & Koronios, 2006). Addressing this issue requires an holistic approach (Brous et al., 2014) which describes the sociological as well as the technological components. As such, the goal of this chapter is to describe and explain the AMDI itself and by doing so to complete the answer to Research Question 4: *What does a model of an AMDI that enables IoT look like?* Figure 6-1 below shows the stage of the research

in which the model build occurs. Having built the knowledge base from a review of literature and exploratory case studies, requirements, propositions and principles were developed in the relevance cycle. In this Chapter we transition to the design cycle in which the build and evaluation of the model occur. Figure 6-1 shows that the build and evaluation phases are iterative. Before testing, the model was built according to the requirements defined by the relevance cycle to level of detail which was deemed appropriate. Chapter 6 describes the final build of the model, however, the model was adjusted slightly during the test phase of the research based on insights provided by the test cases. These adjustments are discussed in Chapter 7 where the test cases are described.

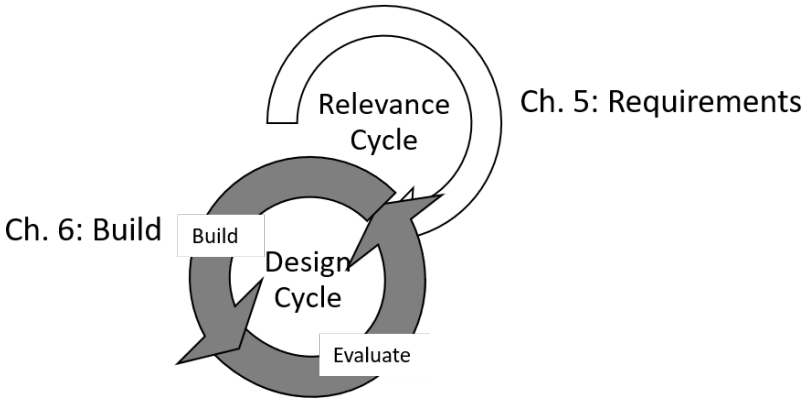


Figure 6-1: The stage of the research in which the model building occurs

The socio-technical complexity of infrastructure systems calls for the combination of object-oriented and agent-oriented perspectives. We therefore adopt the "cross-over" modelling technique (Weijnen et al., 2008). We utilize the autonomous characteristics of agent-based systems in this research to develop an agent based conceptual model of IoT AMDIs for infrastructure management. Agent-based systems provide a decentralized solution based on centralized decision making. This gives the system a high degree of flexibility and robustness (Jennings, 2001).

The conceptual model described in this research aims at helping asset managers understand the nature of data infrastructures in an IoT adoption environment (Sokolowski & Banks, 2010). By modelling data infrastructures, we can illustrate and simulate the basic components of data infrastructures and their interrelationships. The combination of data infrastructure elements and their behaviors make up our agent-based conceptual model. In this chapter we discuss the functional elements of

the AMDI model as identified in the literature review (chapter 3) and the exploratory case studies (chapter 4). As discussed in chapter 5, the knowledge repository used for the model is the domain ontology. Section 6.2 of this chapter discusses how the functional elements are modelled. Section 6.3 of this chapter describes how the components (data, technology and actors) are modelled and section 6.4 describes the schema (data governance). In Section 6.5 describes how the different environments are modelled. Section 6.6 describes the implementation guidelines and discusses how the model may be used in asset management organizations. Section 6.7 concludes the chapter by summarizing the chapter.

### 6.1.1 Modelling Approach

Generally speaking, the most powerful models attempt to minimize the semantic gap between the units of analysis and the constructs present in the modelling approach (Janssen & Verbraeck, 2005). But, with modelling, it is also important to reduce complexity by eliminating unnecessary detail in order to highlight the essence of the problem (Curtis, Kellner, & Over, 1992; Janssen & Verbraeck, 2005). According to Weijnen et al. (2008), the socio-technical complexity of infrastructure systems calls for the combination of object-oriented and agent-oriented perspectives. The "cross-over" modelling technique (Weijnen et al., 2008) forces the modeler to consider problems from the agent perspective, whilst providing insight into the relationship between agents. Therefore, we follow Janssen & Verbraeck (2005) as well as the ideas of agent architectures developed for MAS by Jennings (2001) and develop an agent architecture using object orientation. Object oriented environments require communication between objects (Janssen & Verbraeck, 2005). Implementing an agent within an object orientation requires developing the objects as agents to enable an agent to comply with the common characteristics of agents, such as autonomy, communication, and behavior to either react on the environment or to deliberately perform an action (Janssen & Verbraeck, 2005). According to Janssen & Verbraeck (2005) an agent-based model should ensure that all modeled entities meet the characteristics that make up an autonomous agent. Our model breaks up the AMDI into reusable, logical parts but does not pose a limitation to the extensibility of an element.

### 6.1.2 The AMDI Ontology

We have chosen to use open standard technologies as they are widely accepted. This helps ensure sustainability of the model and allows us to utilize other accepted and popular linked open data ontologies (Jain, Hitzler, Sheth, Verma, & Yeh, 2010). Another advantage of using open standard technologies are the numerous supporting development environments and tooling available which helps us avoid vendor lock-in. In order to ensure interoperability we selected the World Wide Consortium (W3C) standards and recommended Semantic Web technologies (Horrocks, 2008). According to Horrocks (2008), semantic web technologies enable the creation of data stores on the Internet, build vocabularies and write rules for handling data. In this section we apply related W3C Semantic Web technologies to describe the AMDI model.

### 6.1.3 Modelling Language

The model is built using the Resource Description Framework (RDF) as specified by the World Wide Web Consortium (W3C). RDF is a framework for conceptual description or modeling of data (Hayes & Gutierrez, 2004). The RDF data model is based upon the idea of making statements about resources in the form of subject–predicate–object expressions, known as triples (Hayes & Gutierrez, 2004; McBride, 2001). The subject denotes the resource, and the predicate denotes traits or aspects of the resource, and expresses a relationship between the subject and the object. A collection of RDF statements intrinsically represents a labeled, directed multi-graph. According to Harth & Decker (2005), this should make an RDF data model better suited to knowledge representation than other data model types. RDF data is still often used in relational databases as "triple stores".

RDF is a way of recording information about resources (Powers, 2003). As such, the RDF schema (RDFS) imposes very loose constraints on vocabularies whereas an ontology language adds additional constraints that increase the accuracy of implementations of a vocabulary and allow additional information to be inferred about the data (Powers, 2003). According to Gruber (1993, p. 199), an ontology is "an explicit specification of a conceptualization". As such, an ontology formally defines a common set of terms that are used to describe and represent a domain (Heflin, undated). Essentially, the ontology is the definition of the business rules associated with a vocabulary (Powers, 2003). According to Heflin, ontologies make knowledge reusable by encoding knowledge in a domain and also across domains. Although it is theoretically possible to

develop an ontology/vocabulary using just RDFS, this research incorporates ontological elements from the Web Ontology Language (OWL) effort being developed by the World Wide Web Consortium (W3C). As such, we follow the W3C specifications and address four specific concepts with our AMDI model, namely:

- Classes (general things) in the many domains of interest
- The relationships that can exist among things
- The properties (or attributes) those things may have
- Constraints on relationships between the classes and their properties

OWL and its current ongoing version OWL 2 is an ontology language for the Semantic Web with formally defined meaning (W3C OWL Working Group, n.d.). OWL 2 describes the domain in terms of classes, individuals, properties, datatypes and values, and, in broad terms, consists of axioms and facts that describe the domain. OWL 2 uses Internationalized Resource Identifiers (IRIs) as names for classes, individuals, properties and datatypes. Collectively these names are known as entities, which, together with data values, make up the building blocks of OWL 2 ontologies (W3C OWL Working Group, n.d.). In this research we adopt the view that *Classes* are a group of resources with similar characteristics. In the AMDI model, as in RDF and OWL, every class is associated with a set of individuals. The base class "owl:Thing" is a built-in class representing the set of all individuals. *Individuals* represent actual objects from the domain. There are three distinct types of properties: object properties which are used to relate one individual to another; data properties which are used to relate an individual to a data value; and annotation properties which are used to add information, such as comments, to individuals, classes or properties.

The ontology developed by this research is built using Protégé, a free, open-source ontology editor and framework for building intelligent systems developed by Stanford University. Protégé is a Java-based ontology editor which provides the mechanisms to create ontologies and allows the user to save the ontologies as plain text or as JDBC-accessible data-stores and as RDF/XML.

### 6.1.4 Reasoner

The model was corrected in an iterative manner using the HermiT reasoner build 1.3.8.413. HermiT is reasoner for ontologies written using the Web Ontology Language (OWL). HermiT was used during the build of the ontology to determine whether or not the ontology was consistent, for example by identifying subsumption relationships between classes. The

reasoner was run at regular intervals during the build (for example when external ontologies were coupled to the AMDI) to ensure consistency throughout the ontology. HermiT was chosen as it is a publicly-available OWL reasoner based on a "hypertableau" calculus which provides much more efficient reasoning than other algorithms, greatly improving performance and accuracy. Furthermore, HermiT uses direct semantics and passes all OWL 2 conformance tests for direct semantics reasoners.

### 6.1.5 Open Linked Data

As discussed above, there are a number of ontology representation languages available, and using the linked open data approach we are able to extend the model where necessary to include existing ontologies. This has various advantages such as aiding interoperability, increasing credibility of the schema, and improving ease of development (Archer, Loutas, & Goedertier, 2013). In this research we utilize a variety of linked, open ontologies which are discussed as and when they are used. To search for ontologies, we relied on ontology libraries such as the DAML Ontology Library (http://www.daml.org/ontologies)
and the OBO (http://obo.sourceforge.net) which are a listing of knowledge resources (Noy, Rubin, & Musen, 2004). We intend to utilize the ontology metadata such as keywords that describe the topic of ontology content, to build an ontology library where users submit ontology metadata, search for existing ontologies against requirements, and view interrelationships. OWL2 is currently the most popular ontology representation language (Heiyanthuduwage, Schwitter, & Orgun, 2014). As such, RDF/OWL2 provides us with the framework and language for our model. For example, OWL2 provides us with built-in properties for generic classes. The properties of OWL2 are divided in to three disjoint sets, namely *object properties*, *data properties* and *annotation properties*. Object properties relate one individual to another, for example, the object property buy:boughtAt may be used to relate a packet of milk to a store. Data properties relate an individual to a data value, as in, the data property buy:euroPrice may be used to relate a packet of milk to specific euro value (e.g. €2,50). Annotation properties are simple comments which may be added to provide clarity to the class or even the property or ontology itself. We have named our ontology "IoTAMDI" and the ontology has the ontology prefix:
@prefixIoTAMDI: https://github.com/paulbrous/IoTAMDI

Following the linked open data (LOD) concept (Heath & Bizer, 2011), our ontology is loosely coupled with, and makes use of, other ontologies, including:

@prefix foaf: http://xmlns.com/foaf/0.1/
@prefix cube: http://purl.org/linked-data/cube#
@prefix org: http://www.w3.org/ns/org#
@prefix owl http://www.w3.org/2002/07/owl#
@prefix rdf http://www.w3.org/1999/02/22-rdf-syntax-ns#
@prefix rdfs http://www.w3.org/2000/01/rdf-schema#
@prefix xml http://www.w3.org/XML/1998/namespace
@prefix xsd http://www.w3.org/2001/XMLSchema#

Complete descriptions of each of these ontologies can be found at the above links.

### 6.1.6 Summary of the Model Design Approach

Table 6-1 below summarizes how the model complies with the design principles which facilitate communication of the AMDI design as described in section 5.6 and as discussed above. The numbers in the table refer to the relevant design principle described in section 5.6.

Table 6-1: A summary of how the model complies with the design principles which facilitate communication of the AMDI design.

| Design Principle | How the model complies with the principle |
|---|---|
| 1. The model is available in widely accepted open formats. | The model is readable as text or graphic format using widely available open source applications such as Protégé. |
| 2. The model can be edited, stored and recovered for future reference. | The model is easily transferable using a variety of techniques, including download on request, is version controlled, and can be edited with a wide variety of text or graphic based editors. |
| 3. The model illustrates and simulates the basic components of AMDIs and their interrelationships. | The model follows the W3C specifications and address four specific concepts with our AMDI model, namely:<br>- Classes (general things) in the many domains of interest<br>- The relationships that can exist among things<br>- The properties (or attributes) those things may have<br>- Constraints on relationships between the classes and their properties |
| 4. The model combines object-oriented and agent-oriented perspectives, | The model employs a combination of object-oriented and agent-oriented perspectives and develops an agent architecture using object orientation. |

| Design Principle | How the model complies with the principle |
|---|---|
| addressing the socio-technical complexity of infrastructure systems. | |
| 5. The model is extendable where necessary. | The model follows the linked open data approach and we are able to extend the model where necessary to include existing ontologies. |
| 6. The model includes existing, widely accepted ontologies. | The model's ontology is loosely coupled with, and makes use of, other widely accepted ontologies such as FOAF and CUBE. |
| 7. The model uses open, widely accepted modelling schemas and ontology languages. | The model's ontology is loosely coupled with, and makes use of, other widely accepted schema's such as RDFS and XSD. |
| 8. The model follows W3C modelling specifications. | The model uses open standards and widely accepted W3C formats, being built in RDF/OWL format. |
| 9. The model uses open web standards. | The model uses open standards and widely accepted W3C formats, being built in RDF/OWL format. |

## 6.2 Modelling the Main Functional Elements of the AMDI

As discussed in chapter 5, The main elements of the AMDI are the components, data governance and environments. In this section we show how these elements form the basis of the AMDI model. We define the AMDI itself as the class owl:Thing. The classes with the Internationalized Resource Identifiers (IRIs) owl:Thing and owl:Nothing are available in OWL2 as built-in classes with predefined semantics:

- The owl:Thing represents the set of all individuals.
- The owl:Nothing represents the empty set.

RDFS gives a name for the relationship between some specific class and its more general superclass: 'subClassOf' (rdfs:subClassOf). As such, all the AMDI functional elements are, essentially, subclasses of the main class owl:Thing, as seen below in Figure 6-2.

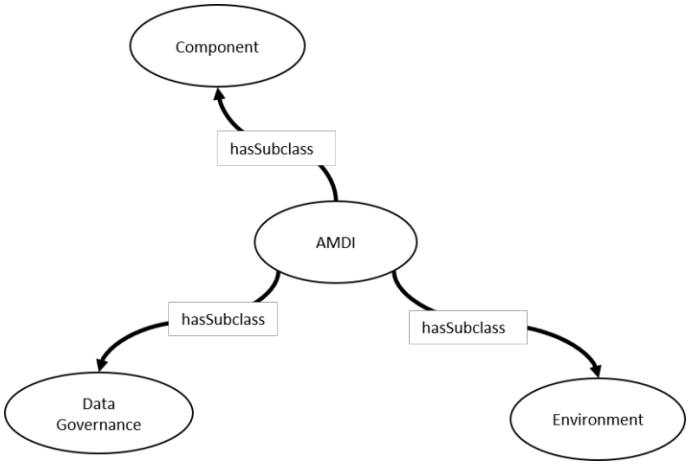


Figure 6-2: The main elements of the IoT AMDI model and their relationships

As seen above in Figure 6-2, the owl:Thing class has been given the annotation property <rdfs:label>AMDI</rdfs:label>. owl:Thing embodies the AMDI but is displayed with the label "AMDI". All the above main classes have be given the object properties iotamdi:Constrains and iotamdi:Enables which indicate the relationship between the classes. The object property iotamdi:Constrains indicates that a class constrains the other classes in its range. The object property iotamdi:Enables indicates that a class enables the other classes in its range.

Following the Duality of Technology theory (Orlikowski, 1992), we notice that technologies, as a product of agents, are enabled and constrained by agents, and that data governance includes the conditions of interaction with technology. We extend the Duality of Technology theory as we notice that the environments in which the infrastructure can be found can also constrain or enable the components and the data governance. Thus the owl:Thing class is also given the object properties: iotamdi:AdaptsToChangeFrom, which indicates that the object is capable of adapting to changes occurring in other classes in its range; iotamdi:EmergentBehaviorInResponseTo, which indicates that this class displays emergent behavior in response to changes in other classes; iotamdi:IsConnectedTo, which indicates that this class displays connectivity; and iotamdi:IsDynamic, which indicates that this class is capable of changing dynamically.

The individual subclasses and their main relationships are discussed in the following sections. We begin in section 6.3 with the subclass, iotamdi:Component which has, in turn, sub-classes

iotamdi:Data, iotamdi:Technology and foaf:Agent. The reader may notice that the sub-class “agent” makes use of the Friend-of-a-Friend (FOAF) ontology (“FOAF Vocabulary Specification,” n.d.). According to the FOAF Vocabulary Specification, FOAF provides a basic "dictionary" of terms for talking about people and the things they make and do. The “Agent” class is the class of agents, or in the words of the FOAF Specification, “things that do stuff”. A well-known subclass is Person, representing people, but other kinds of agents may include *Organization* and *Group*. The Agent class is useful where *Person* is overly specific, such as with chatbots or robots.

In Section 6.4 we discuss the subclass, iotamdi:Environment, which has the subclasses iotamdi:Physical, iotamdi:Cultural and iotamdi:Political. In section 6.5 we discuss the sub-class iotamdi:DataGovernance which has the sub-classes iotamdi:Align, iotamdi:Clarify, iotamdi:Organize, and iotamdi:Comply.

## 6.3 Modelling the Components of the AMDI

In this section we show how these components are related to the component class and how they relate to each other at this level of the model. The iotamdi:Component class is the class of physical or virtual objects which make up the sum of the AMDI. As seen below in Figure 6-3, the class iotamdi:Component has subclasses iotamdi:Data, iotamdi:Technology and foaf:Agent.

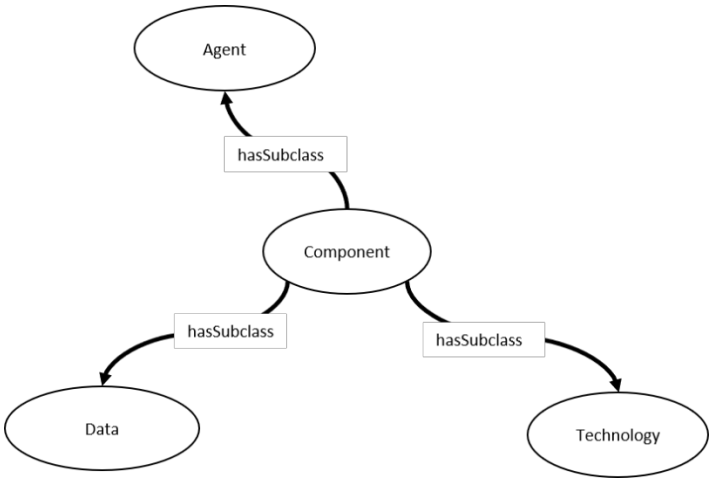


Figure 6-3: The iotamdi:Component class and its subclasses.

Following the Duality of Technology theory (Orlikowski, 1992), we notice that technologies, as a product of agents, are influenced by agents, but that also, technologies extend an influence on agents and the way they behave . We extend the Duality of Technology theory as we notice that data has a similar relationship with technology and agents, both exerting influence on them and being a product of technology and agents. As such we have assigned the object property iotamdi:uses and foaf:made to the agent class, and the object property iotamdi:influences to all three subclasses. The property iotamdi:uses indicates that this class uses classes in its range for a particular purpose. The property foaf:made indicates something that was made by this agent. The property iotamdi:influences indicates that this class has an influence on the classes in its range.

The following sections describe the subclasses of the super-class iotamdi:Component.

### 6.3.1 Data

Data have long been recognized as a core factor in IS and data infrastructures, and have been generally defined as the measure or description of objects or events (Brous et al., 2014; Checkland & Holwell, 1997; Grus et al., 2010; Kettinger & Li, 2010). As discussed in Chapter 1, in our model we follow Ackoff (1971), and define data as symbols which represent the measure or description of objects or events. These data elements as components of data infrastructures are encapsulated in the data class as seen below in Figure 6-4.

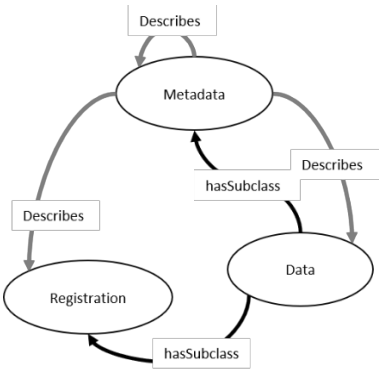


Figure 6-4: The iotamdi:Data class and its sub-classes, iotamdi:Metadata and iotamdi:Registration.

As seen above in Figure 6-4, the iotamdi:Data class has the subclasses iotamdi:Metadata and iotamdi:Registration. As discussed in Chapter 1, metadata is a description of a data entity. The iotamdi:Metadata class has the object property, "Describes". The "Describes" property is a relationship between metadata and the data that the metadata describes. As such, the "Describes" property has the range "Data" (and its subclasses). The "Describes" property has the domain, "Metadata", i.e. having this property implies being a metadata entity, and every value of this property is a metadata entity. Figure 6-5 below depicts the iotamdi:Metadata class and its subclasses.

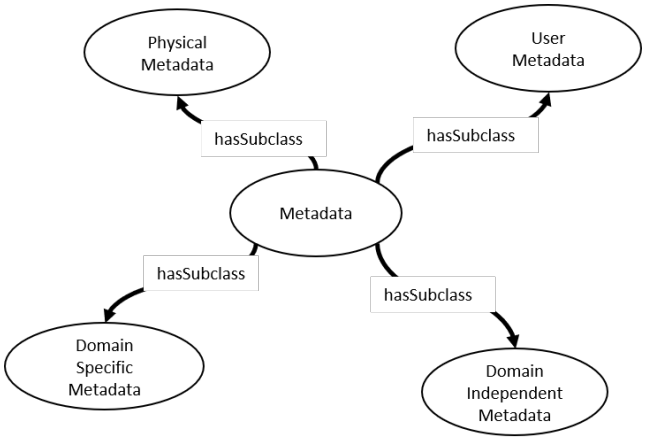


Figure 6-5: The iotamdi:Metadata and its sub-classes

As seen above in Figure 6-5, the iotamdi:Metadata class has the subclasses:"iotamdi:PhysicalMetadata", iotamdi:DomainSpecificMetadata", "iotamdi:UserMetadata", and "iotamdi:DomainIndependentMetadata".

The class iotamdi:PhysicalMetadata includes information about the physical storage of data (Khatri & Brown, 2010). Data properties of this class include, for example:

dc:Format,
iotamdi:MediaType,
iotamdi:digitalOrigin.

The class iotamdi:DomainIndependentMetadata includes generic descriptions such as the creator or modifier of data as well as authorization and lineage information related to the data (Khatri & Brown, 2010). Data properties of this class include, for example: dcterms:Title, dcterms:Subject, dcterms:Language, dcterms:Description. Note that use is made of the Dublin Core Ontology (http://purl.org/dc/elements/1.1 and

http://purl.org/dc/terms/) to extend the data properties of this class. Dublin Core is a moderately small ontology for describing generic metadata which is divided into 2 vocabularies: DC elements and DC terms. "DC elements" contains 15 properties. "DC terms" contains 22 classes and 55 properties.

The class iotamdi:DomainSpecificMetadata provides a set of mappings from a representation language to concepts in the real world (Khatri & Brown, 2010). For example, geospatial metadata is a type of metadata that is applicable to objects that have are associated with some position on the surface of the globe. Data properties of this class include, for example:

iotamdi:SpatialResolution,
iotamdi:TemporalResolution,
iotamdi:CoordinateReferenceSystem.

The class iotamdi:UserMetadata includes annotations that users may associate with data entities. Such annotations can, for example, capture user preferences and usage history (Khatri & Brown, 2010). The class iotamdi:UserMetadata include user attributes (such as user preferences) that do not impact a user's core functionality. Data properties of this class include, for example: foaf:name, foaf:lastName, iotamdi:NumberofViews, iotamdi:Reviewed.

As seen in Figure 6-5 above, the iotamdi:Data class includes the subclass iotamdi:Registration class. The iotamdi:Registration class defines what is generally known as data i.e., as discussed in Chapter 1, the symbols representing measures or descriptions of objects or events. Figure 6-6 below depicts the iotamdi:Registration class which consists of the subclasses iotamdi:Description and iotamdi:Measurement.

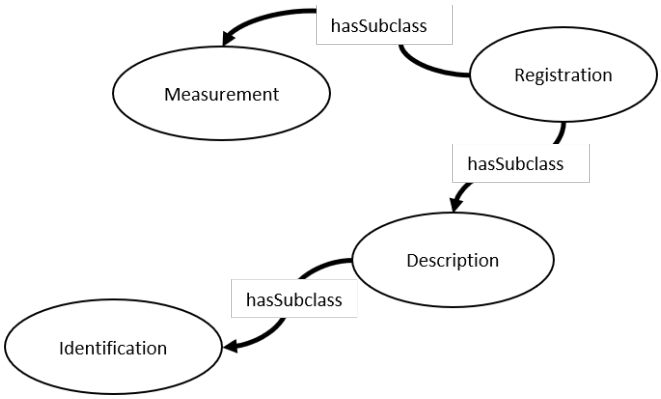


Figure 6-6: The iotamdi:Registration class and its subclasses.

The iotamdi:Registration class includes the object property iotamdi:Represents, which defines the relationship between a registration and the object or event it is representing.

The class iotamdi:Description defines the symbols used register descriptions of objects or events. This class consists of the subclasses iotamdi:Identification and iotamdi:Observation. The class iotamdi:Identification defines the symbols used to uniquely identify an object or event. This class includes the object property iotamdi:Identifies which defines the relationship between the identifier and the object or event to be identified. Data properties of this class include, for example: iotamdi:GUID, and iotamdi:SystemID.

The iotamdi:Observation class defines the symbols used to register observations and sensations of objects or events. This class includes the object property iotamdi:IsObservationOf, which indicates that the symbols represent observations of an object or event. This object property has the sub-properties of: 1. iotamdi:IsAudioOf, which indicates that the symbols represent audio of an object or event; 2. iotamdi:IsVisualizationOf, which indicates that the symbols represent visualizations of an object or event such as video or images; 3. iotamdi:IsChemicalOf which indicates that the symbols represent the chemical compositions of an object or event; and 4. iotamdi:IsTouchOf which indicates that the symbols represent the physical impact of an object or event such as, for example, pressure, level of hardness, or level of roughness.

The iotamdi:Measurement class defines the symbols used register measurements of objects or events. This class includes the object property iotamdi:IsMeasurementOf, which indicates that the symbols represent measurements of an object or event. This object property is extendable to include, for example, sub-properties such as iotamdi:IsTemperatureOf, which indicates that the symbols represent the temperature of an object or event, or iotamdi:IsLengthOf, which indicates that the symbols represent the length of an object or event.

### 6.3.2 Technology

The technology class encapsulates the collection of Information Technology (IT) artifacts, hardware and software, used in the production of data or services or in the accomplishment of objectives, such as data analysis or data management. Creating and managing a business driven IT involves decisions based on a sound understanding of an organization's strategic context (Broadbent & Weill, 1997). IT has led many organizations to imagine a world of leveraged knowledge, but whilst IT

has inspired this vision, it in itself cannot bring it into being (Lesser, Fontaine, & Slusher, 2009). In the AMDI model, IT is regarded as an important enabler of AMDIs. The iotamdi:Technology class and its subclasses, iotamdi:Hardware and iotamdi:Software is depicted in Figure 6-7 below.

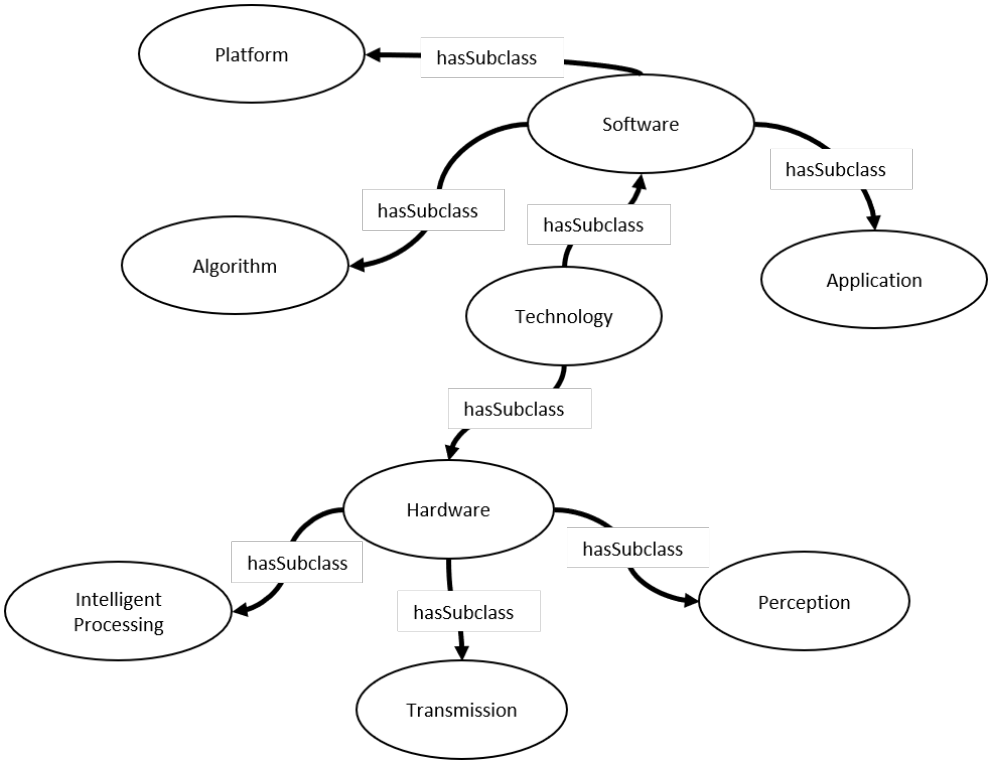


Figure 6-7: The iotamdi:Technology class and its subclasses.

The iotamdi:Technology class defines the collection of IT artefacts, hardware and software used in the production of data or services or in the accomplishment of objectives such as data management or data analysis. This class has two main subclasses, iotamdi:Software and iotamdi:Hardware.

The iotamdi:Software class defines a set of instructions or programs instructing computers within the IoT system to do specific tasks. Software is a generic term used to describe computer programs. The iotamdi:Software class has the subclasses iotamdi:Algorithm, iotamdi:Application, and iotamdi:Platform. The iotamdi:Platform class defines a group of technologies that are used as a base upon which

applications are developed. Computers use specific central processing units (CPUs) that are designed to run specific machine language code. In order for the computer to run software applications, the applications must be in that CPU's binary-coded machine language. As such, IoT platforms both enable and constrain IoT applications. The iotamdi:Application class defines any program, or group of programs, that is designed for the end user. Applications run on platforms. The iotamdi:Algorithm class defines a process or set of rules to be followed in calculations. Algorithms run within applications.

The iotamdi:Hardware class defines the physical parts or components of an IoT system. As the hardware that is used within IoT systems also determines the software used the class iotamdi:Hardware includes the object properties iotamdi:ConstrainCompute, which indicates that the class constrains computation, and iotamdi:EnableCompute, which indicates that the class enables computation. The iotamdi:Hardware class has the subclasses iotamdi:Perception, iotamdi:Transmission, and, iotamdi:Processing. The iotamdi:Perception class includes hardware used for the acquisition of observations or measurements by using perception, acquisition and measurement technology such as RFID, two-dimensional code and sensors, etc. The iotamdi:Transmission class defines the class of hardware that ensures that IoT objects have access to information networks and can realize reliable information interaction and sharing through communications networks. The iotamdi:Processing class defines the class of hardware than enables the analysis of sensor data to achieve intelligent decision-making and control.

### 6.3.3 Agents

As seen below in Figure 6-8, in our model all independent actors are viewed as agents. Agents are encapsulated within the agent class, which can be extended to include a wide variety of types of agents. We adopt Janssen & Verbraeck's (2005) definition of an agents and define the foaf:Agent class as autonomous, goal driven entities that are able to communicate with other agents and whose behavior is the consequence of their (1) observations, their (2) knowledge and their (3) interactions with other agents (Janssen & Verbraeck, 2005).

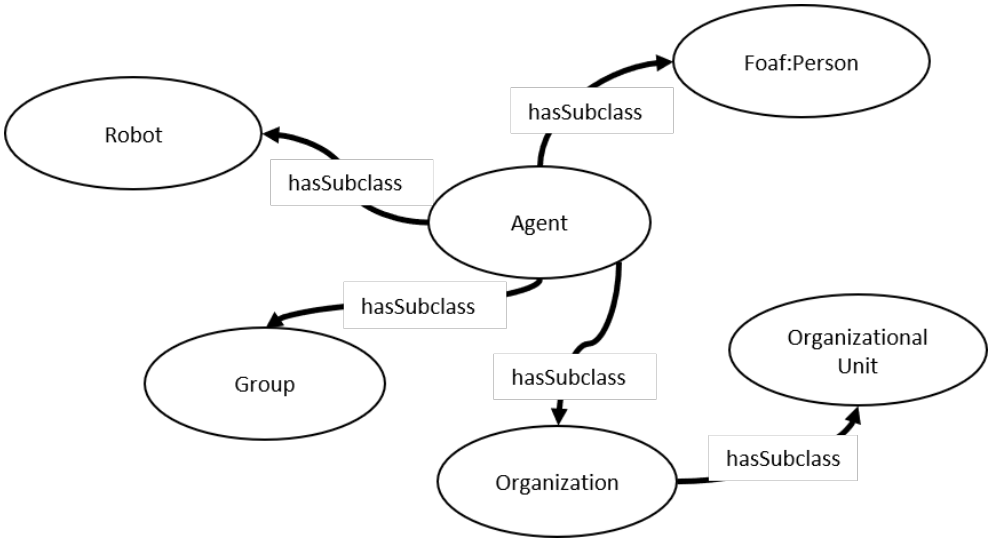


Figure 6-8: The agent class, its subclasses and relationships.

Changes to data infrastructures are structural changes that require the interaction of agents around both technical changes to the data infrastructure, as well changing social values as drivers of change. For example, whilst the rules of the system may be set at the higher levels, by the relevant governance bodies, it often comes down to individuals to interpret and implement these policies at the operational level. As such, the foaf:Agent class has the subclasses foaf:Group, foaf:Person, foaf:Organization, iotamdi:Bot and iotamdi:Robot. The definitions of the foaf subclasses can be found at "http://xmlns.com/foaf/spec/". The iotamdi:Bot subclass defines agents which are software applications that run automated tasks over the Internet. As such this class is also equivalent to the iotamdi:application class. The subclass is a machine capable of carrying out a complex series of actions automatically.

In many multiple agent architectures, complexity is generally reduced and problems are decomposed, with sub-problems being assigned to specific agents (Janssen & Verbraeck, 2005). The greater problem is in this way resolved including multiple agents. Our model follows this line of thinking as each agent has a role to play in the implementation of the data infrastructure, based on their position within the organization and the underlying processes. We thus further develop the agent-based model by examining the characteristics of agents with regards to the underlying schema as described by the data governance class. The data governance class helps to define the nature of agents, as well as shaping the behavior and interactions of agents. Agents are always

situated in an environment. They receive inputs related to the states of their environment, and they act on the environment. Data governance provides the guidelines which guide the actions of the agents. An agent's behavior is often viewed as a manifest of intelligence (Russell & Norvig, 1995). The behavior is modeled in terms of the tasks that need to be accomplished given its position (Janssen & Verbraeck, 2005; Zambonelli, Jennings, & Wooldridge, 2001). According to Janssen & Verbraeck (2005), behavior is dependent on the circumstances, and as a result modeled agents should be able to have various types of behavior. The behavior of the agents dictates which technology is implemented and which data is developed. This behavior also dictates how the data and the technology are maintained.

### 6.3.4 Summary of Model Compliance: Component Principles

Table 6-2 below summarizes how the model complies with the design principles which enhance our understanding of the AMDI design as described in section 5.6 with regards to the components of the AMDI. The numbers in the table refer to the relevant design principle described in section 5.6.

Table 6-2: How the model complies with the design principles which enhance our understanding of the AMDI design with regards to the components of the AMDI.

| Design Principle | How the model complies with the principle |
|---|---|
| 10. The model describes metadata and its relationship to IoT related data. | See figure 6-3: The iotamdi:Data class and its sub-classes, iotamdi:Metadata |
| 11. The model describes IoT related registrations and their relationships. | See figure 6-3: The iotamdi:Data class and its sub-classes, iotamdi:Registration and figure 6-5: The iotamdi:Registration class and its subclasses. |
| 12. The model describes the different forms of metadata and their relationships to IoT data. | See figure 6-4: The iotamdi:Metadata and its sub-classes |
| 13. The model describes hardware related to IoT and their relationships. | See figure 6-6: The iotamdi:Technology class and its subclasses. |

| Design Principle | How the model complies with the principle |
|---|---|
| 14. The model describes software related to IoT and their relationships. | See figure 6-6: The iotamdi:Technology class and its subclasses. |
| 15. The model describes required IoT related application components and their relative functions in the architecture. | See figure 6-6: The iotamdi:Technology class and its subclasses. |
| 16. The model describes the roles of people as agents in the AMDI, their relationships and behavior. | See figure 6-7: The foaf:Agent class, its subclasses and relationships. |
| 17. The model describes organizational groups as agents in the AMDI, their relationships and behavior. | See figure 6-7: The agent class, its subclasses and relationships. |
| 18. The model describes bots and robots as technological agents in the AMDI, their relationships and behavior. | See figure 6-7: The agent class, its subclasses and relationships. |

## 6.4 Modelling Data Governance

The data governance class determines the behavior of the agent and how the agent chooses to organize their activities. The data governance class is depicted below in Figure 6-9. Data governance is a complex undertaking. Because data governance directs the actions of agents in AMDIs, it is insufficient to describe the totality of data governance only in specific data governance classes. Data Governance properties can also be found in a number of object properties which occur in other classes, such as foaf:Role which has the domain foaf:organization and range foaf:Agent.

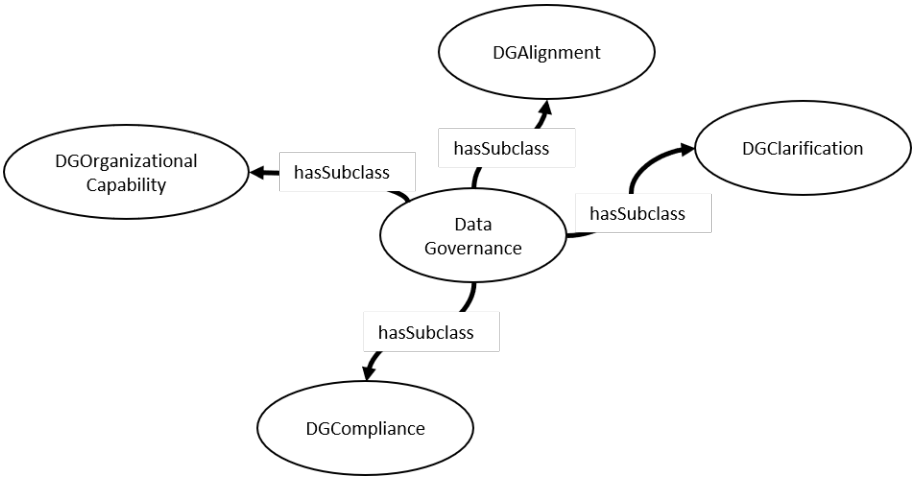


Figure 6-9: The iotamdi:DataGovernance class, its subclasses and relationships.

In the literature and exploratory cases studies we have noticed that principles of data governance should include the data management function and assigning roles and responsibilities, ensuring alignment with business needs, ensuring compliance, and ensuring clarification of how the data infrastructure has been set up, including definition of terms etc. (Brous et al., 2016). As such, the main subclasses of the iotamdi:DataGovernance class include:
iotamdi:DGOrganizationalCapability, which is the class of artefacts required to ensure organization of data governance in a particular organization; ioamdi:DGAlignment, which is the class of artefacts which align data with business needs; iotamdi:DGCompliancy, which is the class of artefacts which ensure that data is compliant with policy, laws and directives; and iotamdi:DGClarification which is the class of objects which ensure clarity over the data landscape within the AMDI.

### 6.4.1 Organizational Capability

As seen below in Figure 6-10, the class, iotamdi:DGOrganizationalCapability includes the subclasses: iotamdi:CoordinationMechanism and iotamdi:DataManagementProcess.

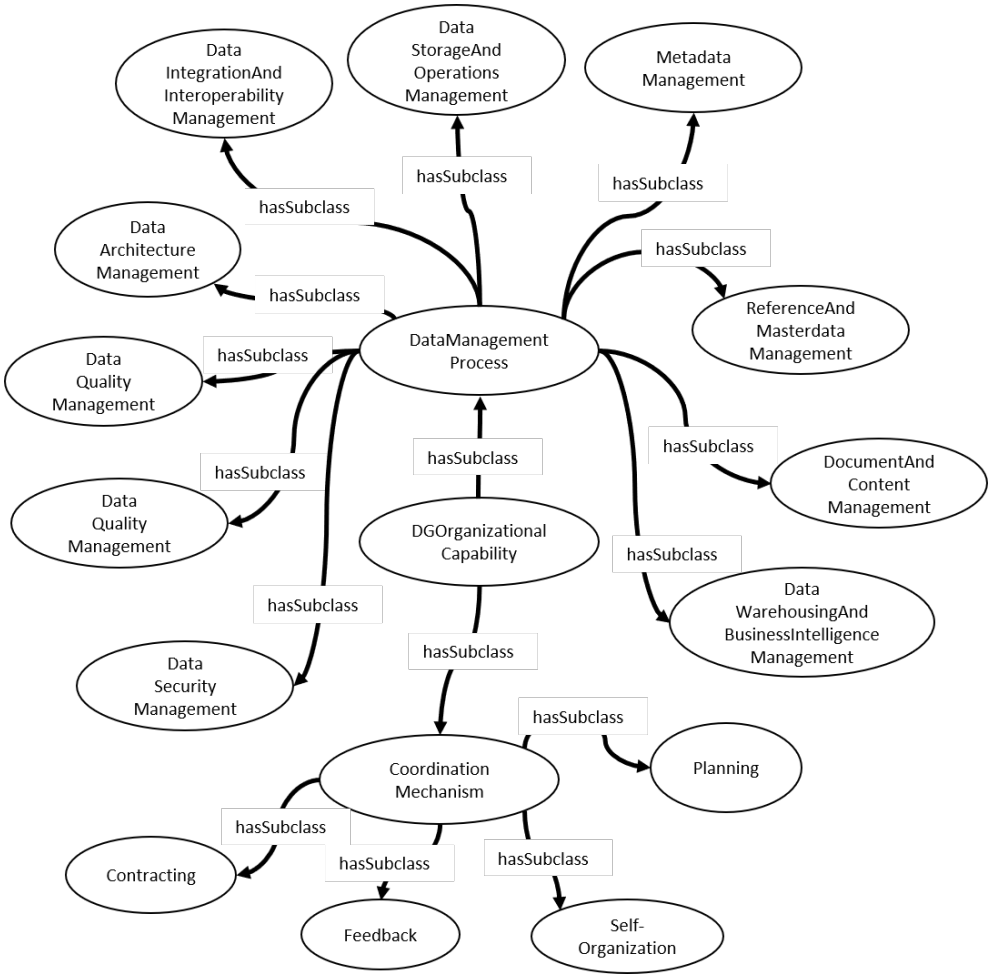


Figure 6-10: The class, iotamdi:DGOrganizationalCapability its subclasses and relationships

An important object property which has iotamdi:DGOrganizationalCapability in its domain includes iotamdi:Organizes which indicates that this class defines the rules for organizing the AMDI. The object property iotamdi:Organizes includes the subproperty iotamdi:Structures, which indicates that the class structures the data governance organization, and the subproperty foaf:Role which assigns roles such as iotamdi:Ownership and iotamdi:Stewardship to agents.

The class iotamdi:CoordinationMechanism defines the coordination mechanisms used to manage data in an organization and includes the subclasses: iotamdi:SelfOrganization which is the coordination

mechanism whereby AMDIs are able to adjust and adapt themselves to both external and internal influences (Grus et al., 2010); iotamdi:Feedback in which AMDIs can use its own output to adjust its inputs and processes (Grus et al., 2010); iotamdi:Contracting in which activities are divided into subtasks that can be performed by specialist agents (Nwana et al., 1996); and iotamdi:Planning in which involves planning to coordinate activities that have yet to be executed (March & Simon, 1958).

The class iotamdi:DataManagementProcess defines the data management processes used to manage data through the AMDI and includes "the business function that develops and executes plans, policies, practices, and projects that acquire, control, protect, deliver and enhance the value of data" (International & Earley, 2011). The professional organization, The Data Management Association International (DAMA), has, besides data governance, defined 10 overriding data management processes: Data Architecture Management, Data Quality Management, Metadata Management, Document and Content Management, Data Modelling and Design, Data Security Management, Data Warehousing and Business Intelligence Management, Reference and Master Data Management, Data Storage and Operations Management, and Data Integration and Interoperability Management. These processes are reflected in the classes: iotamdi:DataArchitectureManagement which includes the "method of design and construction of an integrated data resource that is business driven, based on real-world subjects as perceived by the organization, and implemented into appropriate business environments." (International & Earley, 2011). This class also includes the process of data modelling and design;
iotamdi:DataQualityManagement which includes the "process of ensuring that the development effort will result in the desired product" (International & Earley, 2011); iotamdi:MetadataManagement which includes "processes that create, control, integrate, access and analyze metadata repositories to allow for easier access" (International & Earley, 2011); iotamdi:DocumentAndContentManagement which includes managing "data found outside of standard structured databases" (International & Earley, 2011); iotamdi:DataSecurityManagement which includes "the prevention of unauthorized access to a database and its data, and to applications that have authorized access to databases" (International & Earley, 2011);
iotamdi:DataWarehousingAndBusinessIntelligenceManagement which includes the "operational, administrative and control processes that provide access to Business Intelligence data and support to knowledge

workers engaged in reporting, query and analysis" (International & Earley, 2011); iotamdi:ReferenceAndMasterDataManagement which includes "ensuring consistency with a 'golden version' of data values" (International & Earley, 2011); iotamdi:DataStorageAndOperationsManagement, which includes providing "support from data acquisition to purging" (International & Earley, 2011); and iotamdi:DataIntegrationAndInteroperabilityManagement which includes managing "how data is selected, transformed and flows across databases" (International & Earley, 2011).

### 6.4.2 Alignment

Data governance should also ensure that data is aligned with the needs of the business. As such, the class iotamdi:DataGovernance includes the subclass iotamdi:DGAlignment, which, as seen below in Figure 6-11 includes objects which ensure that data meets the necessary requirements to align with the requirements of the business.

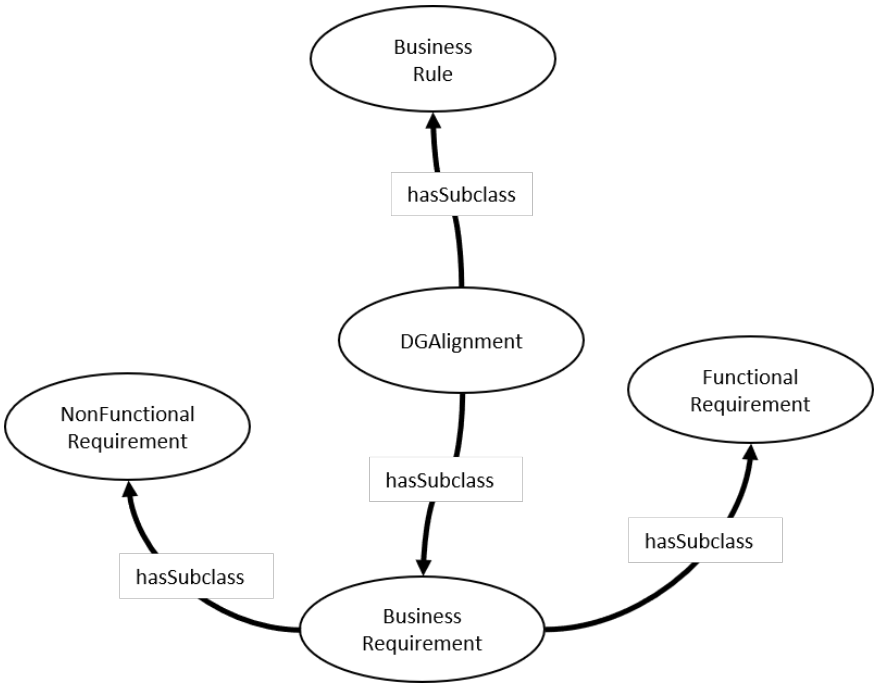


Figure 6-11: The iotamdi:DGAlignment class, its subclasses and relationships

As seen above in Figure 6-11, the class iotamdi:DGAlignment includes the subclasses: iotamdi:BusinessRequirement, which includes the business requirements used to define data capabilities; and iotamdi:BusinessRule, which includes the business rules used to define the functional framework of the data. The reader should note that this class originally was composed of sub-classes defining the different types of business rules, however, during the test phase these classes were deemed to be unworkable.

### 6.4.3 Compliance

Ensuring compliance means defining, monitoring and enforcing data policies (internal and external) throughout the organization. Figure 6-12 below depicts the class iotamdi:DGCompliance, its subclasses and relationships.

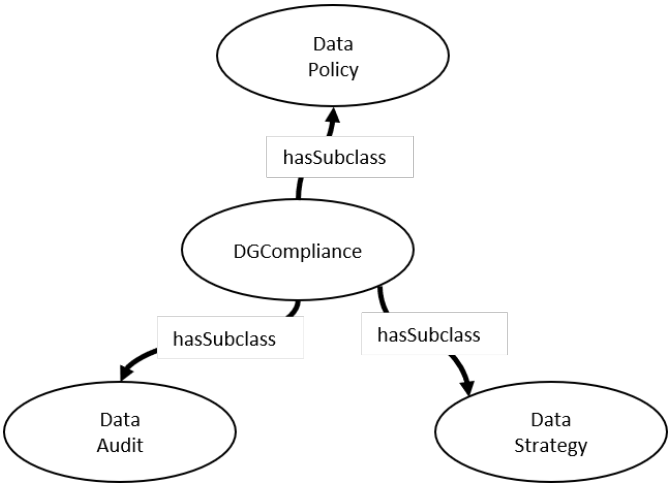


Figure 6-12: The class iotamdi:DGCompliance, its subclasses and relationships.

Establishing and enforcing policies regarding the management of data is important for an effective data governance practice. A data strategy directs the data management organization, and the data audit monitors and controls the compliancy of the organization. As such, the iotamdi:DGCompliancy class includes the subclasses: iotamdi:DataPolicy, which includes an organization's set of data management artefacts designed to assist business administration and protect company assets; iotamdi:DataStrategy, which is "a business plan for leveraging and enterprise's data assets to maximum advantage" (International & Earley, 2011); and iotamdi:DataAudit, which is "a formal and official verification

of quality and conformance to requirements, regulations, standards and/or guidelines" (International & Earley, 2011). Important object properties related to the iotamdi:DGCompliancy class include: iotamdi:Controls which indicates that the object monitors compliancy to norms, policies, laws and regulations; iotamdi:Regulates, which indicates that the object defines the actions required to comply to norms, policies, laws and directives; and iotamdi:Directs, which indicates that the object gives direction to the AMDI.

### 6.4.4 Clarification

But governing data appropriately is only possible if it is properly understood what the data to be managed means, and why it is important to the organization (Brous et al., 2016). As such, Figure 6-13 below depicts the iotamdi:DGClarification class and its subclasses.

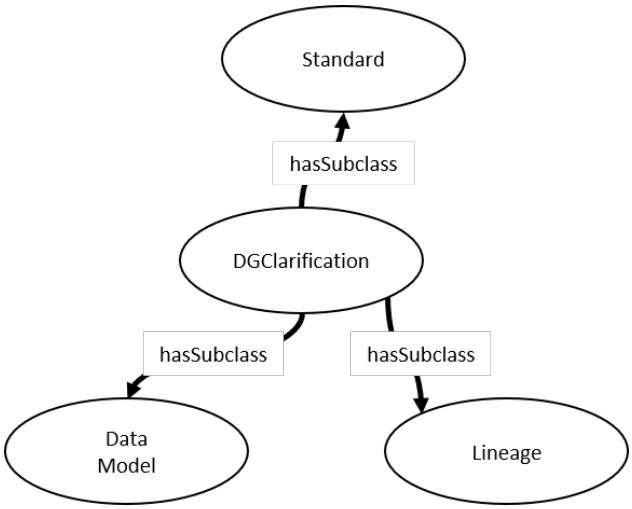


Figure 6-13: The iotamdi:DGClarification class, its subclasses and relationships.

As can be seen in Figure 6-13 above, the iotamdi:DGClarification class by definition clarifies data, and as such is equivalent to metadata. However, the iotamdi:DGClarification also describes other components of the AMDI and therefore includes the AMDI in its range. The iotamdi:DGClarification class includes the subclasses: iotamdi:Lineage, which includes objects which clarify the data and other components of the AMDI; iotamdi:DataModel, which includes a description of elements of data and standardizes how they relate to one another and to properties of the real world entities; and the subclass iotamdi:Standard, which

includes objects that standardize components and relationships of the AMDI. Important object properties of the iotamdi:DGClarification class include: iotamdi:Clarifies which indicates that the objects clarify the components of the AMDI – note that iotamdi:Clarifies is equivalent to the object property iotamdi:Describes; iotamdi:MaintainsDescendency, which indicates that the object maintains lineage of data; iotamdi:Models, which indicates that the object models (an aspect of) the AMDI; and iotamdi:Standardizes, which indicates that the object standardizes (an aspect of) the AMDI.

### 6.4.5 Summary of Model Compliance: Data Governance Principles

Table 6-3 below summarizes how the model complies with the design principles which enhance our understanding of the AMDI design regards to data governance. The numbers in the table refer to the relevant design principle described in section 5.6.

Table 6-3: How the model complies with the design principles which enhance our understanding of the AMDI design regards to data governance

| Design Principle | How the model complies with the principle |
|---|---|
| 19. The model describes the organization of data governance. | See Figure 6-10: The class, iotamdi:DGOrganization its subclasses and relationships. |
| 20. The model describes the loci of data provenance. | The object property iotamdi:Organizes includes the subproperty iotamdi:Structures, which indicates that the class structures the data governance organization, and the subproperty foaf:Role which assigns roles such as iotamdi:Ownership and iotamdi:Stewardship to agents. |
| 21. The model describes appropriate coordination mechanisms positively associated with IoT adoption. | The class iotamdi:CoordinationMechanism defines the coordination mechanisms used to manage data in an organization and includes a number of subclasses describing the various coordination mechanisms positively associated with IoT adoption. |
| 22. The model describes artefacts and relationships which ensure that IoT related data meets the necessary requirements to align with the requirements of the business. | See Figure 6-11: The iotamdi:DGAlignment class, its subclasses and relationships. |

| Design Principle | How the model complies with the principle |
|---|---|
| 23. The model includes a data strategy as object, and describes processes to develop and implement the strategy. | The iotamdi:DGCompliancy class includes the subclass: iotamdi:DataStrategy, which is "a business plan for leveraging and enterprise's data assets to maximum advantage" (International & Earley, 2011); |
| 24. The model describes the use of standards to align IoT data and technology with the needs of the asset management organization. | See Figure 6-13: The iotamdi:DGClarification class, its subclasses and relationships, including the sub-class iotamdi:Standard |
| 25. The model uses standardized data management frameworks to describe data management activities related to IoT processes. | The class, iotamdi:DGOrganization includes subclasses and relationships which are derived from best practices as described by the Data Management Association (DAMA). |
| 26. The model describes objects which monitor compliancy to norms, policies, laws and regulations | The iotamdi:DGCompliancy class includes the subclasses: iotamdi:DataPolicy, which includes an organization's set of data management artefacts designed to assist business administration and protect company assets; |
| 27. The model describes a set of data management artefacts designed to assist business administration and protect company assets. | See the class iotamdi:Controls which indicates that the object monitors compliancy to norms, policies, laws and regulations; iotamdi:Regulates, which indicates that the object defines the actions required to comply to norms, policies, laws and directives; and iotamdi:Directs, which indicates that the object gives direction to the AMDI. |

## 6.5 Modelling the Environments

Although data governance should be recognized as the schema which guides actors operating within and acting on the data infrastructure, it should also be recognized that data governance should be practiced in accordance with the environments within which the data infrastructure finds itself. As such, the organization of data governance should not be a "one size fits all" approach and the data governance organizational structure should fit with a specific organization. Figure 6-14 below depicts the environment class which often influences the boundaries, form and evolution of data infrastructures.

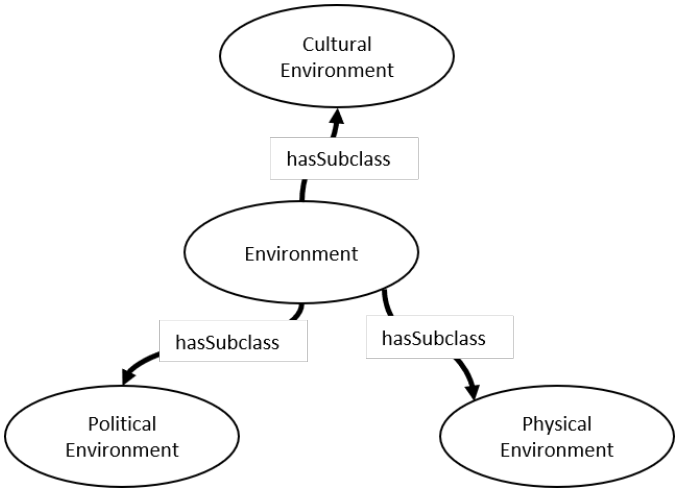


Figure 6-14: The iotamdi:Environment class, its subclasses and relationships

According to de Man (2006), the goals of data infrastructures are to facilitate and coordinate exchange, sharing, accessibility, and use of data and encompass complexes of interacting institutional, organizational, technological, human, and economic resources. The potential of data infrastructures to facilitate access to, and sharing and communication of, spatial data may be subject to existing cultural, political and societal factors (de Man, 2006). For example, actors may want to maintain their powerful positions and prevent others from direct access to the data infrastructure. Taken a step further, Kim & Kaplan (2006) believe that the weak "cause-and-effect" exchanges seen within data infrastructures may be due to the interpretation of context. Actors are therefore non-passive. A data infrastructure is thus more than a series of socio-technical interactions, but is made up of actors forced to act on a changing landscape (R. M. Kim & Kaplan, 2006). As such, as seen above in figure 6-3-5, the class iotamdi:Environment includes the subclasses: iotamdi:PhysicalEnvironment, which includes the sum of the tangible things in the area within which the AMDI occurs; iotamdi:CulturalEnvironment, which includes beliefs, practices, customs and behaviors that are found to be common to all agents operating within the AMDI; and iotamdi:PoliticalEnvironment, which includes governing objects which affect the operations of the AMDI. Important object properties within the environment domain include iotamdi:Influences which indicates that the environment influences how the object may behave.

### 6.5.1 Summary of Model Compliance: Environment Principles

Table 6-4 below summarizes how the model complies with the design principles which enhance our understanding of the AMDI design as described in section 5.6 with regards to the components of the AMDI. The numbers in the table refer to the relevant design principle described in section 5.6.

Table 6-4: How the model complies with the design principles which enhance our understanding of the AMDI design with regards to the environments of the AMDI.

| Design Principle | How the model complies with the principle |
|---|---|
| 28. A description of the physical environment is an integral part of the AMDI. | The subclass iotamdi:PhysicalEnvironment, includes the sum of the tangible things in the area within which the AMDI occurs. |
| 29. The model assimilates potential effects of the physical environment on the AMDI. | The object property iotamdi:Constrains indicates that the subclass iotamdi:PhysicalEnvironment constrains the other classes in its range. The object property iotamdi:Enables indicates that this class enables the other classes in its range.<br>The object properties: iotamdi:AdaptsToChangeFrom, indicates that the object iotamdi:PhysicalEnvironment causes changes occurring in other classes in its range; iotamdi:EmergentBehaviorInResponseTo, indicates that the object iotamdi:PhysicalEnvironment causes changes occurring in other classes in its range; |
| 30. A description of the cultural environment is an integral part of the AMDI. | The subclass iotamdi:CulturalEnvironment includes beliefs, practices, customs and behaviors that are found to be common to all agents operating within the AMDI. |
| 31. The model assimilates potential effects of the cultural environment on the AMDI. | The object property iotamdi:Constrains indicates that the subclass iotamdi:CulturalEnvironment constrains the other classes in its range. The object property iotamdi:Enables indicates that this class enables the other classes in its range.<br>The object properties: iotamdi:AdaptsToChangeFrom, indicates that the object iotamdi:CulturalEnvironment causes changes occurring in other classes in its range; iotamdi:EmergentBehaviorInResponseTo, indicates that the object iotamdi:CulturalEnvironment causes changes occurring in other classes in its range; |
| 32. A description of the political environment is an integral part of the AMDI. | The subclass iotamdi:PoliticalEnvironment includes governing objects which affect the operations of the AMDI. |

| Design Principle | How the model complies with the principle |
|---|---|
| 33. The model assimilates potential effects of the political environment on the AMDI. | The object property iotamdi:Constrains indicates that the subclass iotamdi:PoliticalEnvironment constrains the other classes in its range. The object property iotamdi:Enables indicates that this class enables the other classes in its range.<br>The object properties: iotamdi:AdaptsToChangeFrom, indicates that the object iotamdi:PoliticalEnvironment causes changes occurring in other classes in its range; iotamdi:EmergentBehaviorInResponseTo, indicates that the object iotamdi:PoliticalEnvironment causes changes occurring in other classes in its range; |

## 6.6 Summary: Modelling Behaviors

Table 6-5 below summarizes how the model complies with the design principles which enhance our understanding of the behavior of the AMDI. The numbers in the table refer to the relevant design principle described in section 5.6.

Table 6-5: A summary of how the model complies with the design principles which enhance our understanding of the behaviors of the AMDI.

| Design Principle | How the model complies with the principle |
|---|---|
| 34. The model assimilates dynamic change in relationships, behavior and individuals into its design. | The owl:Thing class is given the object property iotamdi:IsDynamic, which indicates that this class is capable of changing dynamically. |
| 35. Every object has a significant relationship with at least one other object in the model. | The owl:Thing class is given the object property iotamdi:IsConnectedTo, which indicates that this class displays connectivity. Each object in the model has a significant relationship with a superclass which leads ultimately to the superclass owl:Thing |
| 36. The model is configurable and reconfigurable to assimilate specific, local requirements. | The owl:Thing class is given the object property iotamdi:AdaptsToChangeFrom, which indicates that the object is capable of adapting to changes occurring in other classes in its range. |
| 37. The model is configurable and reconfigurable to assimilate unforeseen behavioral changes of local agents. | The owl:Thing class is given the object property iotamdi:EmergentBehaviorInResponseTo, which indicates that this class displays emergent behavior in response to changes in other classes. |

## 6.7 Implementation Guidelines

This section outlines guidelines for implementation of the IoT AMDI model, which include the rationale, and policy, procedures, and standards for the use in asset management organizations. Modeling is a common process within IT. Organizations which produce and review data models before moving forward with system development may benefit by identifying and resolving some of the issues before implementation as well as developing mature sets of requirements.

### 6.7.1 Use

The AMDI model will primarily be of interest to asset managers wishing to adopt IoT for asset management purposes. The intent of the AMDI model is to ensure that the understanding of the asset management system is as complete as possible, and to provide a way to communicate this knowledge to all stakeholders.

The AMDI model is a conceptual model which includes standardized diagrams and descriptions of the AMDI objects and their relationships. The AMDI model allows asset managers to anticipate and understand problems which may arise in the adoption of IoT for asset management purposes. The model may also be used to aid the development and maintenance of IoT systems in asset management organizations.

### 6.7.2 Personalization

As discussed in the literature review of chapter 3, there can be no "one-size-fits-all" solution to a wicked problem such as understanding asset management through IoT (Weber et al., 2009). As such, the AMDI model presented in this research should be "personalized" to fit each particular organization. The AMDI model presented in this research is at the conceptual level and is extendable in that classes and subclasses can be added or removed according to local needs. The model also represents classes and object properties, and does not pay close attention to data properties or individuals. This allows the local implementation to be configured to the local situation. As such, attention during implementation should be paid to the following when using this model in real world situations.

*Standard Notation*

In this research the notation is constrained by the use of RDF and the presentation possibilities allowed by Protégé. Because the number of

objects in the AMDI model cannot be clearly shown on one page, the model has been split into object groups. An object group has a business coherence, and may be relatively distant from other entities. This grouping allows for scalability and flexibility in the model. Names for the objects should be meaningful and should not conflict with other object names. All objects have instances. As such, the first sentence of the object definition describes a noun with phrases which summarize the meaning of the object, and typical examples are included where possible. This allows the reader to understand the rationale for the object.

### 6.7.3 Governance

The adoption process should outline how the logical and physical models are produced and reviewed during the development of systems. Data governance responsibilities outline the persons or organizational roles responsible for each object group. The intent of the AMDI model is to document a common understanding of the data to be stored and delivered in the data infrastructure.

*Model Planning*
At the start of the adoption program, broad requirements for the minimum viable product should be established. The number and size of logical models which flow out the conceptual AMDI should be determined and the appropriate standards should be identified. The model planning session should be held early in the program, well before formal requirements are resolved.

*Model Reviews*
A review should be scheduled once a significant number of logical models has been created. The review should look at how the models meet the standards, and document any issues which may impact the rest of the organization. The model should be approved when identified deviations from standards have been corrected. An appropriate issue management system should be incorporated.

## 6.8 Summary

This chapter presents a model of AMDIs which is designed to enhance our understanding of asset management through IoT and to facilitate communication between stakeholders. As such this chapter completes the answer to research question 4 which asks *what does a model of an AMDI that accommodates IoT look like*? The model makes use of the RDF

framework and is based on the principles developed in Chapter 5. The design principles are based on requirements gathered during the literature review (chapter 3) and the exploratory case studies (chapter 4) and the design propositions. In this chapter we described the AMDI model providing class diagrams for entity display groups. A complete summary of the classes of the AMDI model can be found in Appendix A. The reader should note that only classes particular to the AMDI model are summarized in Appendix A. The reader should refer to the relevant ontology (see section 6.1) for descriptions of classes described in other ontologies. The model is tested using cases in Chapter 7. These test cases follow the method of personalization and operationalization as described above in section 6.6.

# Chapter 7 Test Cases

*"For my part, I have walked about the streets,*
*Submitting me unto the perilous night,*
*And, thus embraced, Casca, as you see,*
*Have bared my bosom to the thunder-stone;*
*And when the cross blue lightning seemed to open*
*The breast of heaven, I did present myself*
*Even in the aim and very flash of it."*

**- William Shakespeare (Julius Caesar: Act-I, Scene-III)**

## 7.1 Introduction

In Chapter 6 we described a model of AMDIs which accommodate IoT. The AMDI model is designed on the basis of three design propositions. We arrived at these propositions through means of a literature review and three exploratory case studies in which we confirmed the duality of IoT in asset management organizations and the necessity of viewing AMDIs as CAS when adopting IoT. To summarize the propositions, we propose that the components, data governance and environments of the AMDI will improve understanding of asset management though IoT. The model described in Chapter 6 therefore is designed to improve our understanding of asset management through IoT.

Investigating whether the model improves our understanding of asset management through IoT requires testing its efficacy. In this Chapter, we therefore test the usability of the AMDI model and the usefulness of the model. Figure 7-1 below shows that the test cases were performed once the model was deemed to be of a suitable quality. In the course of the test cases, input was received from the participants and re-worked into the model. An example of this is the removal of specific types of business rules from the model. Our tests are conducted within the context of three test case studies. According to Yin (2009), the use of case study research in performing evaluations is derived from the desire to gain an in-depth examination of a phenomena within its real-world context. In this way, case study evaluations are able to capture the complexity of the case, and should be able to attend to contextual conditions (Yin, 2009). As such, the main objective of this chapter is to

answer the final research question, RQ 5: *how does the AMDI model improve understanding of asset management though IoT?* We answer this question by means of three tests:

1. First, we test the validity of the case studies with regards to the criteria for case study selection (see Table 2-1). The results of this test can be found in Table 7-5.
2. Second, we test the usability of the model (see Table 2-5). The results of this test can be found in Table 7-7.
3. Third, we test the design propositions. Essentially, this test is an extension of test two, in that these tests test the *usefulness* of the model. Usefulness is often viewed as being a characteristic of usability (Rubin & Chisnell, 2008). The criteria used for this test are described in Table 7-1 below. The results of this test can be found in Table 7-7.

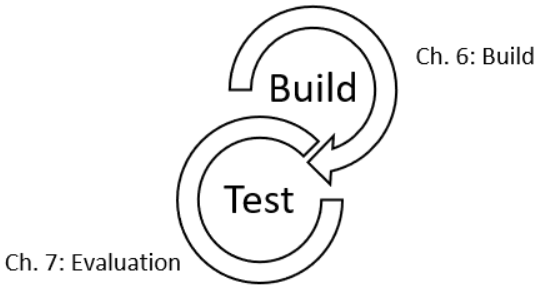


Figure 7-1: Stage of the research wherein the test cases occur

Testing the design propositions required describing the case studies in terms of the model, and discussing these results with subject matter experts in the asset management organizations. We asked the subject matter experts what insights the model could give us with regards to anticipating changes to technology, organization and people. We then collated these results, and related them to the design propositions using the logic described in Chapter 2.

This chapter reads as follows: first the method used to describe the case studies is described and explained in section 7.2. In sections 7.3, 7.4 and 7.5 the three exploratory cases are introduced one by one. Section 7.3 describes the Weigh-in-Motion (WIM) case which is national and managed by RWS. Section 7.4 describes the Smart Meter case which is regional and managed my Stedin. Section 7.5 describes the Hoog Dalem case which is local and managed by Stedin. Section 7.6 discusses the

results of the tests and draws conclusions about the usability of the model. Section 7.7 summarizes this chapter.

Table 7-1: Test 3 - The criteria for testing the usefulness of the model

| Number | Criteria | Reason for Criteria |
|---|---|---|
| 1. | The model should demonstrate that adoption of IoT in asset management is a result of specific influences and not the result of chance circumstances only. | Internal validity: Usefulness Testing the null hypothesis. |
| 2. | The model should provide actionable insights into the influence of people on asset management through IoT. | Internal validity: Usefulness Testing Design Proposition 1: Configuring the elements of AMDIs to accommodate IoT adoption improves understanding of asset management through IoT. |
| 3. | The model should provide actionable insights into the influence of technical innovation characteristics on asset management through IoT. | Internal validity: Usefulness Testing Design Proposition 1: Configuring the elements of AMDIs to accommodate IoT adoption improves understanding of asset management. |
| 4. | The model should provide actionable insights into the influence of data governance on asset management through IoT. | Internal validity: Usefulness Testing Design Proposition 2: Implementing data governance improves understanding of asset management through IoT. |
| 5. | The model should provide actionable insights into the influence of socio-political environments on asset management through IoT. | Internal validity: Usefulness Testing Design Proposition 3: Configuring AMDIs to accommodate cultural, physical and political environments improves understanding of asset management through IoT. |

## 7.2 Approach of the test cases

Following the suggestions of Yin (2009), as part of the larger evaluation, each case described in this chapter describes more closely the entities (classes) described in the model. This is done by identifying so-called "individuals" for each of the sub-classes which allows us to flesh out the model for a particular case and describe the relationship between the entities, offering an explanation of the relationships between the entities

and demonstrating how the cases worked to produce their individual desired outcomes.

The case studies are described in the following way. First a short description of the case is given so that the reader is aware of the context and the desired outcomes of each individual case. Then the case is described according to its components (data, technology and agents), with a description of the individuals depicted in the model. Then the cases are described in terms of data governance (schema) as described in Chapter 6. Finally each case is described in terms of the environments in which each case can be found. The cases are described in the following order: first Weigh-in-Motion, then Smart Meter, and finally Hoog Dalem.

In order to prepare the organization for the case study research project, both Stedin and RWS were provided with information material outlining the objectives of the project. Following the advice of (Yin, 2009), multiple data sources were used. RWS and Stedin allowed the researchers unrestricted access to subject matter experts and internal documentation for all the cases. This helped ensure the construct validity of the case studies (Yin, 2009). Participants were selected on the basis that they were intimately involved in the project as early adopters. Participants were selected from three levels in the organization, namely the strategic, tactical and operational. The cases were investigated over a period of eighteen months for RWS and six months for Stedin. In accordance with accepted recommendations on case study research (Yin, 2009), multiple sources were used for data collection. At the start of the research, in June 2015, group discussions were held at RWS with personnel directly involved in the implementation project or who were tasked with managing and maintain the systems. In January 2017, individual interviews were held with RWS personnel during the implementation process. Workshops were held at Stedin between June 2017 and January 2018. The participants were asked to evaluate the correctness of the model and provide feedback as to the usability of the model. During the workshops, insights provided by the model were noted and collated across the case studies with a view to testing the usefulness of the model. These insights were then listed in relation to the design propositions. All workshops were documented in writing.

For all three cases, internal documentation was selected which dealt with issues faced by the adopting projects. The documents were then analyzed and transferred into an integrated case document (one for each case). The first versions of this document were then sent to the interview participants for feedback and clarification of open points. Once all the additional information feedback had been incorporated, the final

version was reviewed and discussed with the main contacts at RWS and Stedin. Triangulation of data found within the cases was made by listing individuals found in internal documentation and comparing these to the suggestions exposed in the interviews. There were several iterations throughout the research as the cases introduced new individuals. Table 7-2, Table 7-3, and Table 7-4 show the data sources used in the three test case studies.

During the test case studies, the researcher not only observes, but also becomes involved in the theory application and the testing of improvements. Following Janssen, (2001), evaluation in this context means that data was gathered on opinions of the developed model. As our interest was in testing the usability of the model, once the necessary content data had been collected, we organized 1 hour workshops in which we worked with the subject matter experts in the organization to assess the model for the specific cases. We then gathered opinions from the subject matter experts regarding the usability of the model and the insights obtained during the completion of the model.

Table 7-2: Data Sources of Case Study 4: Weigh-In-Motion

| **Data Sources Type** | **Data Sources** |
|---|---|
| Interviews | June 2015: Group discussion<br>Division Head<br>Project manager<br>Data manager<br>Functional manager |
| | October 2015: Individual Interviews<br>Enterprise Architect<br>Program Manager Data Management<br>Coordinator Data Management and Data Quality<br>Data Manager<br>Domain Architect Infrastructure Management<br>Project Manager BIM |
| | January 2017: Individual interviews<br>Program Director<br>Business Analyst<br>Project Manager<br>Service Delivery Manager<br>Project Manager |

| Data Sources Type | Data Sources |
|---|---|
| Documents | A3 Weigh in Motion 03-10-2013 versie 3<br>Wegwijzer Wegbeheer 2005-2010<br>Handboek vast onderhoud<br>Brochure assetmanagement binnen Rijkswaterstaat<br>Aspecten van beheer<br>https://www.rijkswaterstaat.nl/over-ons/nieuws/nieuwsarchief/p2014/10/Informatiesysteem-spoort-overbeladen-trucks-op.aspx<br>TNO (2013) Beladingsgraden vrachtverkeer WIM |

Table 7-3: Data Sources of Case Study 5: Smart Meters

| Data Sources Type | Data Sources |
|---|---|
| Interviews | June – December 2017:<br>Enterprise Architect<br>Information Manager Assets<br>Data Manager<br>Project Manager Smart Data<br>Senior Advisor Asset Management<br>Senior Advisor Risk Analyst |
| Documents | Geplaatste slimme meter<br>handleiding_slimme_meter_communicatie_landis (1)<br>profielen Elektriciteit 2018 versie 1.00.csv<br>profielen elektriciteit versie 1.00 readme.docx<br>Verslag profielen 2018 versie 1.00.pdf<br>https://www.stedin.net/slimme-meter |

Table 7-4: Data Sources of Case Study 6: Hoog Dalem

| Data Sources Type | Data Sources |
|---|---|
| Interviews | Enterprise Architect<br>Information Manager Smart Energy<br>Data Manager<br>Project Manager Smart Data Management<br>Senior Advisor Asset Management<br>Senior Policy Advisor |
| Documents | Eindrapport Hoog Dalem DEF<br>USEF The Framework Implemented - Implementation Guidelines<br>USEF The Framework Implemented - Installation Manual<br>USEF The Framework Implemented - System Architecture<br>USEF PrivacySecurityGuideline_3nov15<br>USEF TheFrameworkSpecifications_4nov15<br>Final Report Hoog Dalem - v0.9 - 24-11-2017 |

For the evaluation test cases, we also wanted to gather opinions from the people involved in the development and application (the design process) of the test cases. This was done by means of unstructured interviews and observations. The reasons for choosing unstructured interviews and observations was because the number of people involved in the design process was low, and because we were particularly interested in the arguments behind the evaluations. This form of data collection is particularly susceptible to bias due to the intrinsic influences of the researcher and other parties involved. Also, the number of persons actively involved in the design process is not high. Therefore, to validate our findings, we also needed to collect the evaluations of persons not directly involved with the development and application of the model. This was achieved by eliciting the opinions of experts to evaluate the concepts behind the model, and by eliciting the opinions of stakeholders. In the interest of privacy, the results and observations were anonymized across the participants and across the cases. To increase the reliability of the case studies, the results of the data collection were organized within the case study database. Following Yin's (2003) advice, the database consists of two separate collections. The first collection included the data collected (evidentiary base) and the second collection included the researcher's reports.

## 7.3 Weigh-in-Motion: Rijkswaterstaat

The first test case, case study number 4, is the WIM system, a national network of monitoring points, managed by RWS. The WIM system is one of the most advanced overloading measurement systems in the world. In the period 2010-2013, RWS built a nationwide network of WIM stations, a total of 22 measuring stations. In addition to sensitive sensors, cameras are also part of the WIM systems. The WIM network, consisting of measuring stations in the road on which the axle loads of heavy traffic is weighed, is used to support the enforcement of overloading by helping the enforcement agency to select overloaded trucks for weighing in a static location.

At present, RWS estimates that at least 15 percent of freight traffic on the Dutch national road network is overloaded. Overloading of heavy vehicles causes road pavement structural distress and a reduced service lifetime (Bagui, Das, & Bapanapalli, 2013). Effectively reducing overloading reduces the damage to the road infrastructure, lengthening the road's lifetime and reduces the frequency of maintenance. The

damage to pavements and installations by overloaded trucks in 2008 was estimated to be at least 34 million euros per year. In addition, the extra maintenance required creates a significant amount of traffic disruptions. These disruptions are estimated to cost several million euros per year. The ambition of RWS is to increase the operational efficiency and effectiveness of the approach to overloading and thus reduce maintenance costs. Traditional enforcement of laws and regulations regarding overloading involved the use of physical measuring stations. This included manual checks by the police in which many vehicles were selected where overloading was suspected but uncertain. This often led to unnecessary inconvenience to citizens as vehicles were often stopped unnecessarily. It was also suspected that "many carriers could avoid these stations by choosing alternative routes whilst retaining their economic gain". In response, RWS has created a national network of 10 monitoring points, the "Weigh in Motion" (WIM) network. Figure 7-2 below shows the position of the main WIM stations in the Dutch highway system.


Figure 7-2: Map of the Main WIM Measuring Stations in The Netherlands (https://www.ilent.nl/documenten/publicaties/2013/11/08/overzicht-weegpunten-in-nederland accessed: 29-11-2017)

### 7.3.1 Components: Data

Data on overloaded vehicles on the road are automatically sent from WIM to the Real-Time Monitor (RTM) web application which processes, stores and publishes the data of all weigh points. Sensors measure the axle loads of passing trucks and loops to measure the speed and length. Cameras above the road register the license plates and Kemler plates (hazard labels). The risk class and a substance identification number are stated on an orange, rectangular sign. The Risk Identification Number (GEVI), also known as the Kemler number or code, is always stated above the substance identification number. The symbols in the risk code largely correspond with the substance classes. WIM metadata is made available as part of the "Area" file periodically supplied to the National Georegister (NGR) by RWS. The metadata is supplied in open standard format as specified by the Open Geographic Consortium (OGC). Figure 7-3 below depicts the WIM AMDI from a data perspective.

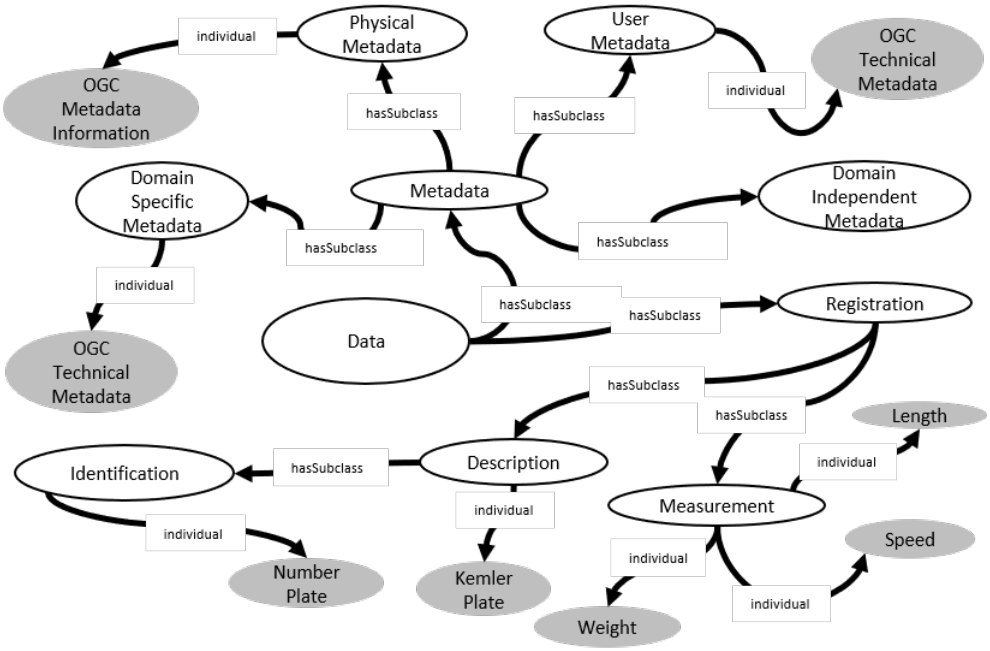


Figure 7-3: The WIM AMDI from a data perspective

Based on this data, the Inspectorate for the Living Environment and Transport (ILT) is able to perform supervision and enforcement actions on overloaded vehicles in near-real time (within 10 seconds),

improving the overall flexibility of the services as ILT and RWS can decide where and when offenders are controlled. The network provides access to information about the actual load of the main road, and about peak times when it comes to overloading. This provides RWS and ILT with the ability to collect information concerning the compliance behavior of individual carriers as, in addition to sensors, cameras are also part of the WIM systems. Via camera footage, the ILT can identify the license plates of vehicles that are overloaded and therefore the detect owner and / or licensee and address. The strategy being to tackle overloading by integrating roadside enforcement along with targeting carriers according to behavior based on the information from the system.

### 7.3.2 Components: Technology

An enforcement chain is a mission critical system, where accuracy and reliability are essential. RWS faces and has faced a variety of impediments and challenges during the implementation and maintenance of the WIM network with regards to accuracy and reliability of the data. Configuration of the system is a delicate process. The WIM system can differentiate between the vehicle and the load, but not all vehicles weigh the same. Not all number plates are placed in the same place on the vehicle, and not all drivers have the same driving style. It is necessary to be able to account for drivers who drive very close to other vehicles, or those who change lanes during inspection (and thus have wheels in two different lanes). The configuration is closely monitored, but, according to an RWS official, "a structured learning cycle with regards to data quality is still required". Some sources have questioned whether "the reliability of the data is sufficiently well equipped" and some interviewees raised questions about the quality of the data. According to an RWS official, "the quality of the data needs to be quantified, and solving data quality issues is incident driven". RWS project managers also cited several technological challenges "due to IT infrastructure limitations which needed to be overcome, and which no single market partner could supply at the time". IoT generates large amounts of data and this data needs to be processed near to real time so that inspectors can quickly identify trucks for roadside inspection. Data from each WIM station are sent via the National Traffic Information and Communications Network, RWS's internal roadside data communication network. The WIM Management Tool (WIM Beheer Tool) supports management of the WIM sites.

The WIM Data Access System is an interface for collecting vehicle data directly from the sites. The WIM roadside systems perform several data processing activities, which include isolating license plate images

from raw camera images, analyzing axle/vehicle weight measurements, filtering data using predefined threshold or business rule limits, integrating static weight data to perform quality checks for WIM system calibration, and producing vehicle registrations. The data can be accessed through WIM monitors via laptop computers and remote, secure access to support real-time preselection of noncompliant vehicles. RWS's internal data communication network allows for integration of the data with other internal databases, including a pavement management database (Winfrabase) and the database maintained by the Transport Inspectorate. Figure 7-4 below depicts the WIM IoT AMDI from a technology perspective.

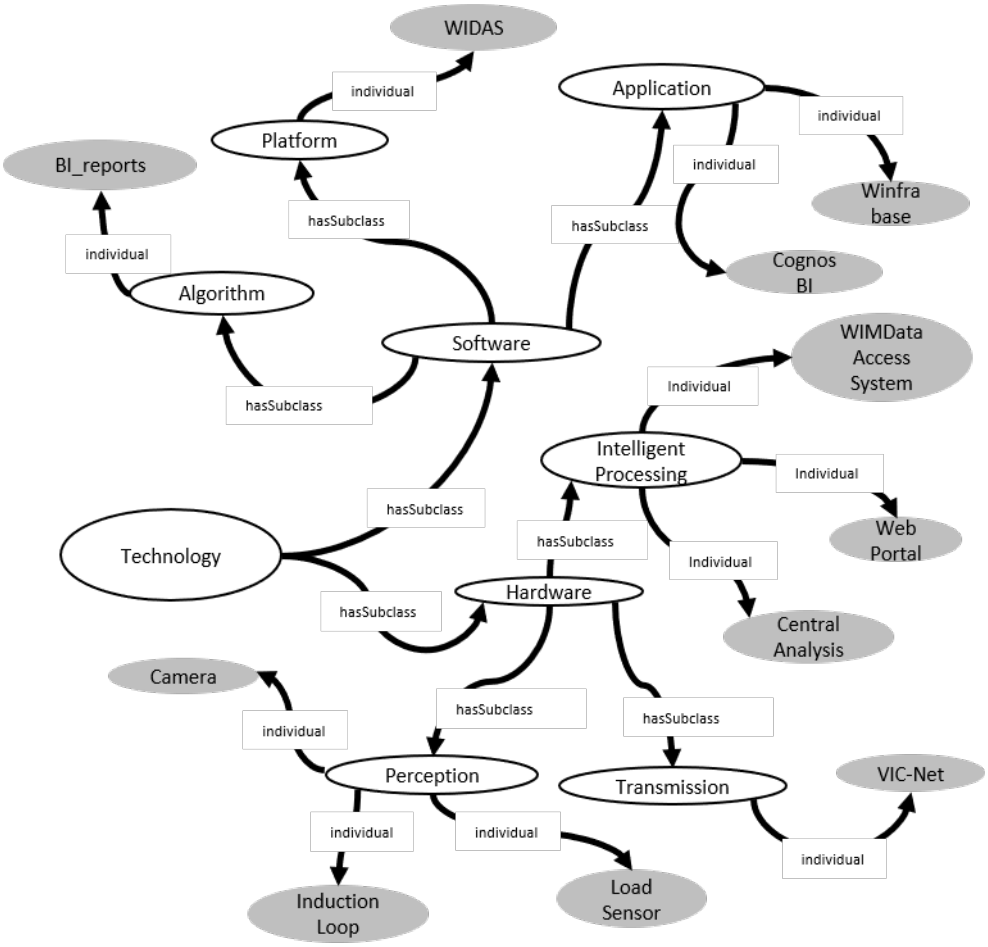


Figure 7-4: The WIM AMDI from a technology perspective

Data can be accessed directly through the RWS Intranet. RWS's Business Intelligence reporting tool allows RWS personnel to extract personalized WIM data reports, nonfiltered or filtered according to vehicle size, vehicle weight, vehicle weight compliance status (i.e., compliant/noncompliant), vehicle class, or other, depending on need.

### 7.3.3 Components: Agents

To maintain their asset management data system, RWS has developed a data management organization which implements and enforces uniform data entry and data management protocols and processes. This data management organization encompasses a wide variety of agents. Within the data management process, there are many different organizational levels, each level and each link in the information chain acting as an agent in the process. For example, divisions of RWS are organized according to geographic location, and each division is an independent agent. Each independent division implements standardized processes in their own way, and each individual advisor, in his turn, can act independently. As an organization, RWS contracts out a good deal of the data entry to external contractors, who in turn are also agents. This means that RWS does not always have full control of the data entry process. Figure 7-5 below depicts the main agents in the WIM AMDI.

RWS personnel extract personalized WIM data reports according to their requirements. A small staff is responsible for managing and maintaining the WIM data management system. A part of their duties is to provide data to RWS colleagues. RWS's Centre for Transport and Navigation relies on this data to conduct research and analyses and offer policy recommendations to the Ministry of Infrastructure and The Environment. National Police personnel at a mobile enforcement site receive real-time data and video information. The officer at the mobile enforcement site contacts on-road colleagues to intercept the overloaded vehicle and escorts it to the mobile weighing station for further inspection by an Inspector from the Transport Inspectorate. Onsite, the truck's individual axles are weighed using static scales and modest registration and safety checks are performed. Importantly, the inspection process is still performed manually, no robotic agents were revealed during the research.

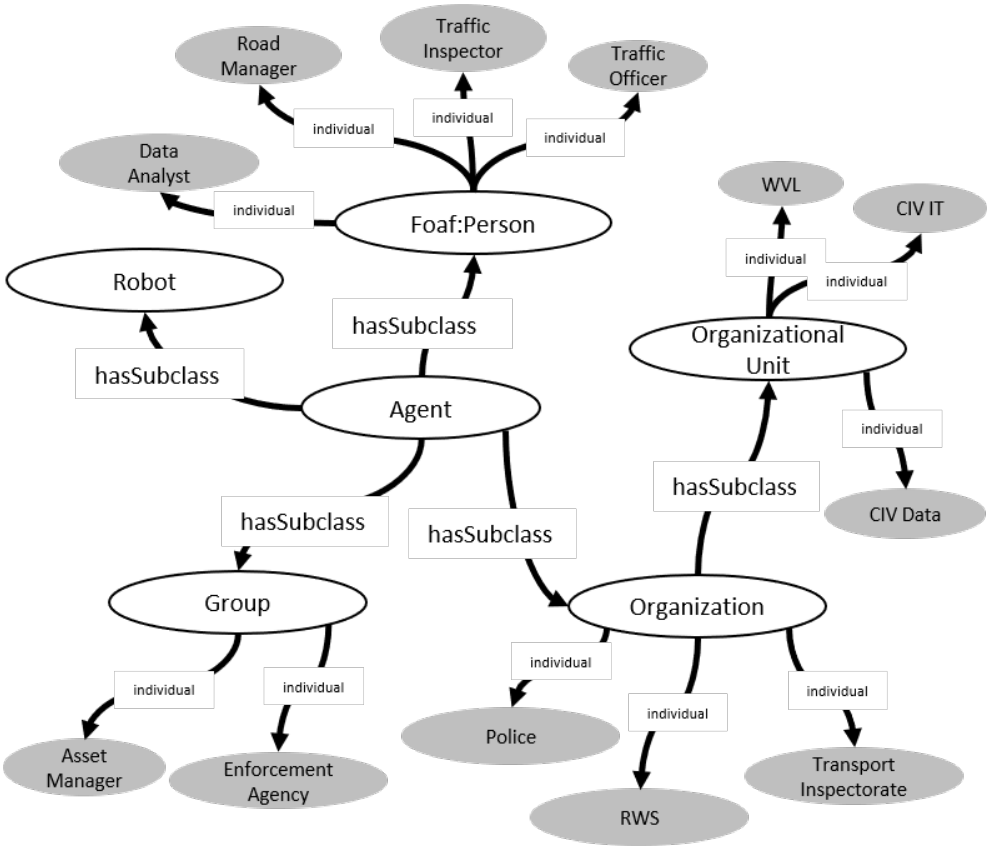


Figure 7-5: The WIM AMDI from an agent perspective

### 7.3.4 Data Governance

RWS is looking more and more towards an integral approach to managing the entire network of assets. According to a RWS official, "an integral approach to managing the network of assets helps us know better the quality that we desire from the performance of the assets." As such, the Information Delivery Specification (IDS) is a part of the contract between RWS and the contractor in which the data transfer is specified. This contract document guarantees a uniform exchange of information on structures between the different partners. RWS has formally accepted the contract method as the coordination mechanism of choice. Also, planning through the implementation of yearly portfolio plans is an important coordination mechanism. But depending on the level of organization and independence of the agent, other, less formal coordination mechanisms such as self-organization and feedback have also become important

behavioral tools. Figure 7-6 below depicts the organizational capabilities of WIM data governance.

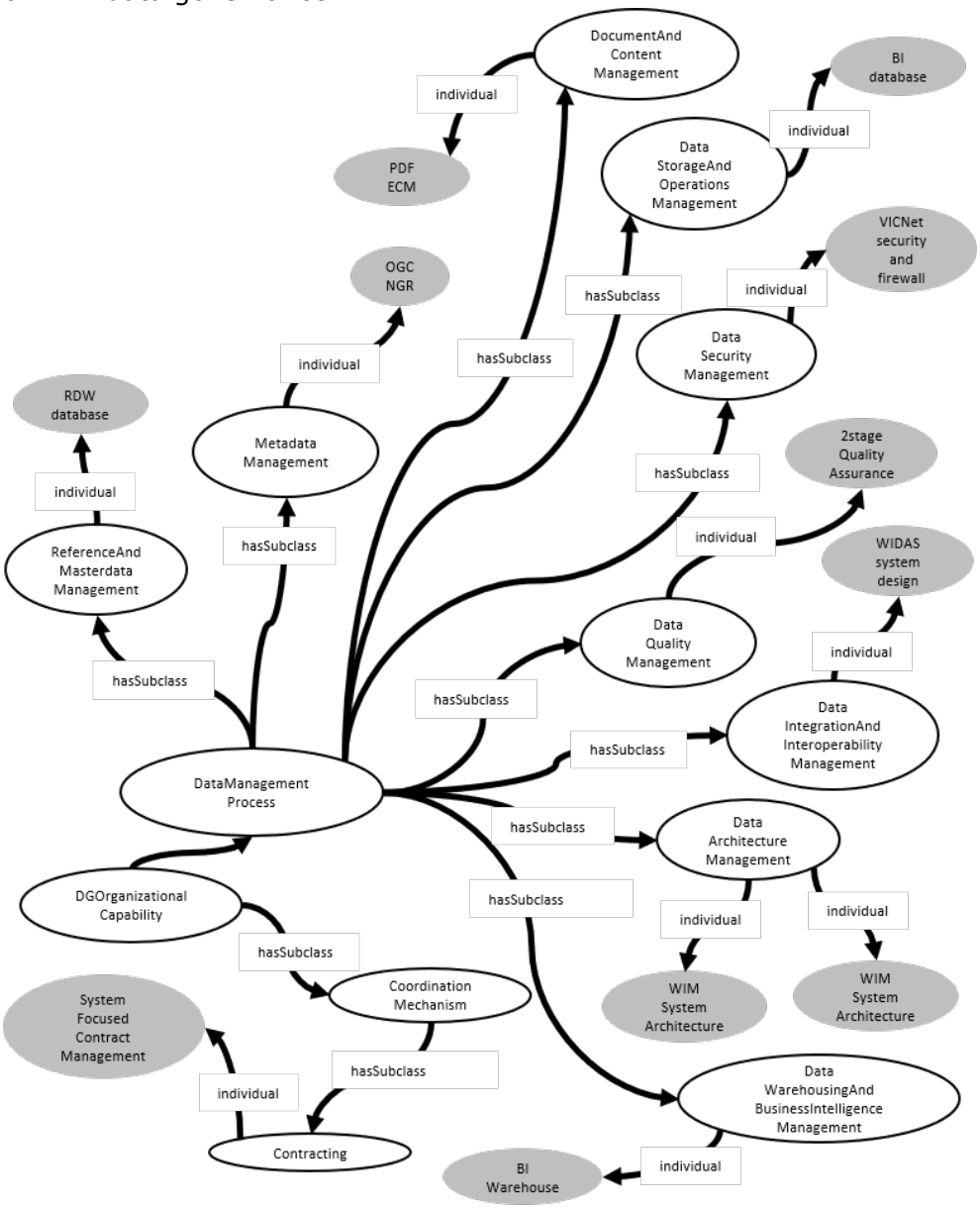


Figure 7-6: Organizational capabilities of the WIM AMDI

Stakeholder requirements of WIM have been carefully described by RWS and can be described as the development of an axle load

measuring system that can be used as a measure for direct enforcement of overloading. The enforcement of overloading is carried out by the National Police and the Traffic Inspectorate. According to RWS, Weigh-In-Motion in combination with Video is an "efficient tool for standing and preventive approaches to overloading enforcement". The disadvantage remains that this method is still very labor intensive because the static (stationary) considerations remain necessary. Similarly, component and behavioral requirements are also captured in multiple documents but can be summarized as follows:

- Detecting a vehicle
- Measuring the dynamic axle loads by multiple sensors
- Predicting the static axle pressures and the mass of the vehicle on the basis of the dynamic measurements
- Determining whether there is overloading on the basis of the vehicle type.
- Filtering out possible incorrect measurements

Figure 7-7 below depicts the alignment aspects of data governance in the WIM AMDI.

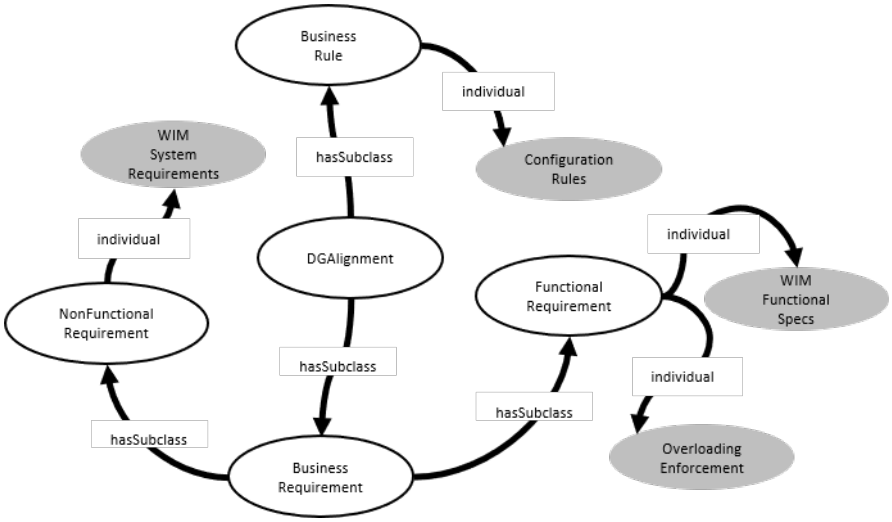


Figure 7-7: Alignment aspects of data governance in the WIM AMDI

The ability to detect overloaded trucks is based on data and it is possible to ensure owners of the carriers and load are also identified and thus enforce regulations at source. With regards to improving planning and maintenance, RWS's strategy was to outsource the operational side of WIM to external contractors which meant that divisions which

previously did the work of weighing and monitoring vehicles needed to be reorganized to do other work. RWS initially outsourced the management of the system. However, RWS has since rescinded that decision due to clashes in planning with other processes such as traffic management. According to a RWS Director, "in order to effectively manage the technology, it is important to have sufficient mandate to manage the entire chain". Managing only the technology or parts of the system produces inefficiencies and can disrupt other processes, such as traffic management, if the overview of the system is not considered when planning maintenance. Figure 7-8 below depicts the clarification aspects of data governance in the WIM AMDI.

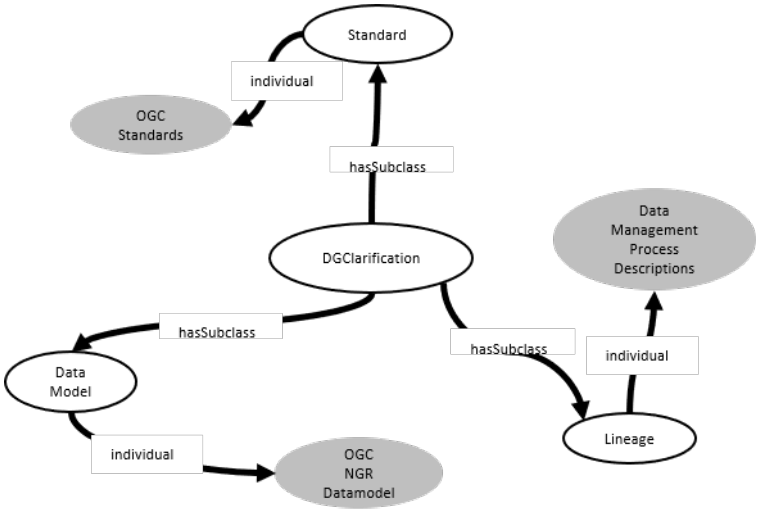


Figure 7-8: Clarification aspects of data governance in the WIM AMDI

RWS and the Transport Inspectorate have been able to improve the efficiency of regulations as they are able to perform administrative enforcement through administrative fines for repeat offenders which are far in excess of the penalties for individual offenders. WIM can differentiate between the load and the vehicle. It is possible to identify not only the transporter, but also the owner of the load. Enforcement of regulations is therefore greatly improved. One of the initial challenges of the WIM project was the definition of the service and the identification of possible solutions. Initial proof of concepts used a combination of intermediate products to approximate the final solution. According to officials, "this led to several interoperability and integration issues which needed to be overcome".

Figure 7-9 below depicts the compliance aspects of data governance in the WIM AMDI. RWS noticed that the adoption of WIM has led to new products being offered by companies who may not necessarily be established partners of RWS and to the loss of old products being offered by more established partners. This has led to new streams of revenue for private parties. New revenue streams for the government also became clear as, according to RWS officials, implementing WIM has "led to a higher chance of catching actual offenders and better effectiveness of controls". The duality of achieving new revenue streams is that, not only implementation costs, but also maintenance costs of the WIM network are high as the sensors often come loose in the asphalt and the repair of the damage is very expensive.

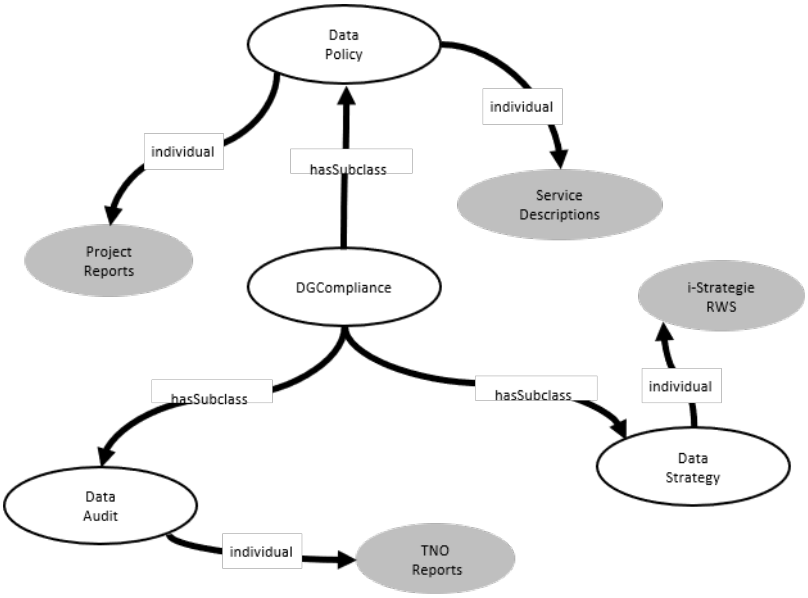


Figure 7-9: Compliance aspects of data governance in the WIM IoT AMDI

### 7.3.5 Environments

Innovation was required in order to be able to ensure the required precision of the data required. Tensions arose as to where responsibility for innovation lay. Being a public sector organization, RWS did not wish to give market advantage to a single private sector party, but was also unwilling to develop the innovation internally. Introducing new technology to the market empowered citizens to develop new products and created

new business opportunities. But the duality was that a RWS Director expressed concern about "the impact of the adoption of WIM by RWS on the private sector and conflicting market forces which WIM has introduced". As there are few private organizations capable of implementing WIM, if RWS would provide innovation opportunities to a single party, this would have provide that party with an unfair market advantage. The RWS Director explained that "it is important to develop a procurement strategy with regards to IoT adoption". In this case, cooperation with the universities was sought to develop the required innovation. With the help of universities in the Netherlands, a proof of concept was developed, the results of which were made publicly available. Figure 7-10 below depicts the WIM AMDI from an environmental perspective.

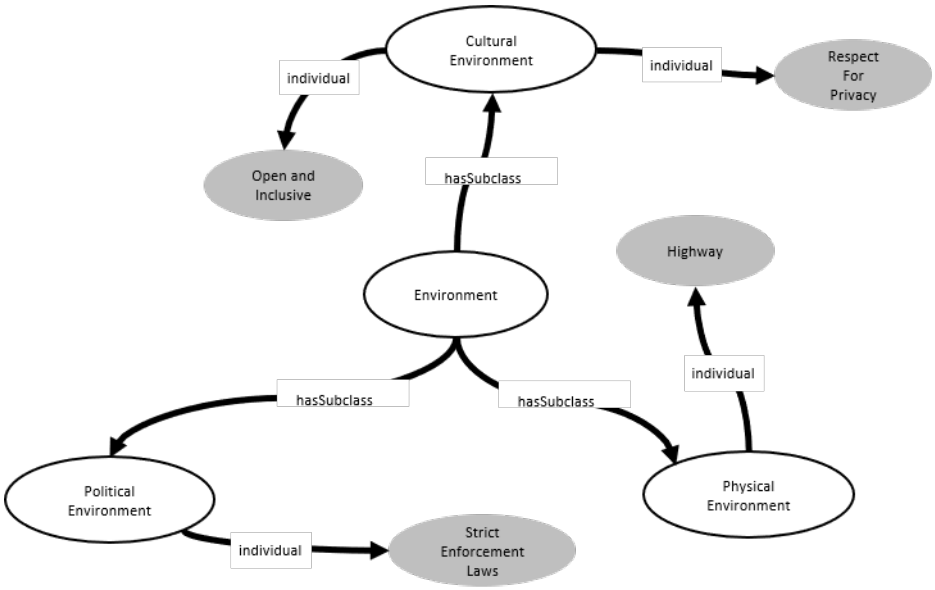


Figure 7-10: The WIM IoT AMDI from an environmental perspective

The conflicting market forces created by the new demand has meant that RWS needed to rethink their approach to framework agreements with established parties. There are different perceptions of the level of ambition pursued by the WIM project. The WIM function has gradually changed from being a tool used to apprehend offenders to being a tool used for digital inspection. Analysis of the stored measurement data shows patterns, improving forecasting and trend analysis. There is obviously something wrong with vehicles that are frequently flagged in

the system. That may be a reason to perform roadside inspections in a subsequent inspection or to visit the parent company for an inspection. The duality attached to the gain provided by being able to identify offenders, is the necessity for ensuring data privacy and data security. Any images or other data created by the system which are made publicly available need to ensure anonymity. Furthermore, security of the data is of vital importance due to the importance of being able to prove offence. It must not be possible in any way to tamper with the "evidence" provided by the data. It is not yet possible to entirely automate the enforcement process, as physical testing is still required to legally prove overloading. The Dutch legal system does not yet fully trust WIM to provide legally conclusive evidence with regards to overloading. An RWS official suggested that "as an instrument to help roadside enforcement WIM works well, but there are difficulties in using WIM to legally prove offence". A new legal framework is required before this system is legally acceptable in The Netherlands.

## 7.4 Smart Meters: Stedin

Our second test case, case 5 – Smart Meters is the management of energy distribution through the use of smart energy meters. The smart meter is a new generation meter. It is digital and registers and stores energy consumption automatically. Meter readings are automatically forwarded to the energy supplier. A smart meter records usage of electricity and/or gas in intervals and communicates that information at back to the utilities company. Smart meters gather data for remote reporting. Smart Meters looks at the management of energy distribution by a distributed system operator, in this case, Stedin, through the utilization of the Smart Meter.

Stedin manages and develops energy (electricity and gas) networks in the Rotterdam and Utrecht regions. They are responsible for the electricity and gas connections from the high voltage and high pressure networks to homes and businesses up to the gas and electricity meters installed at site. Stedin also does the maintenance and repair of the grid, remedies malfunctions and takes care of the installation of new connections. As such, the smart meter is used in asset management to determine capacity and breakages in the electrical grid. Stedin has noticed the trend towards reducing $CO_2$ emissions by switching to electricity as the primary source of energy. Stedin believes that a smart electrical grid that better balances the supply and demand of energy is an important link to improving the energy grid so that it can be used more efficiently and that energy supply can remain affordable.

Stedin is a regulated organization, meaning that although not officially a government organization, it does have a monopoly which means that charges are regulated and the organization is monitored by the Consumer and Market Authority. Figure 7-11 below depicts the area in which Stedin is operating smart meters. Stedin has connected the gas meter (wireless or with a cable) to the electricity meter, and, as such, both meters can be read remotely. The smart electricity meter has a communication module that transmits both the meter readings for electricity and gas. The smart meter is an important link in the smart energy grid by provides insight into the energy flows, such as where more energy may be needed or where disruptions occur.

Figure 7-11: The regional areas managed by Stedin with Smart Meters (https://www.stedin.net accessed: 2018)

### 7.4.1 Components: Data

In addition to expected data such as energy usage levels, other forms of data are also made available through the smart meter. The smart meter display shows when a grid operator has communicated with the meter and what data has been removed from the meter. There are specific laws regarding remote readable measuring devices. The end-user is the legal owner of the data, and as such can check the meter read out in accordance with agreements with the service operator. For example, the end-user has the possibility to check that the service operator does not read out more measurement data than is allowed. The meter also stores a description indicating whether the meter readings are to be transmitted to the network operator or not, and if yes, how many meter readings have been transmitted. This 'logbook' is stored for a year in the smart meter. The log data can be read out locally by the end-user or by engaging a customer expert. Figure 7-12 below depicts the Smart Meter AMDI from a data perspective.

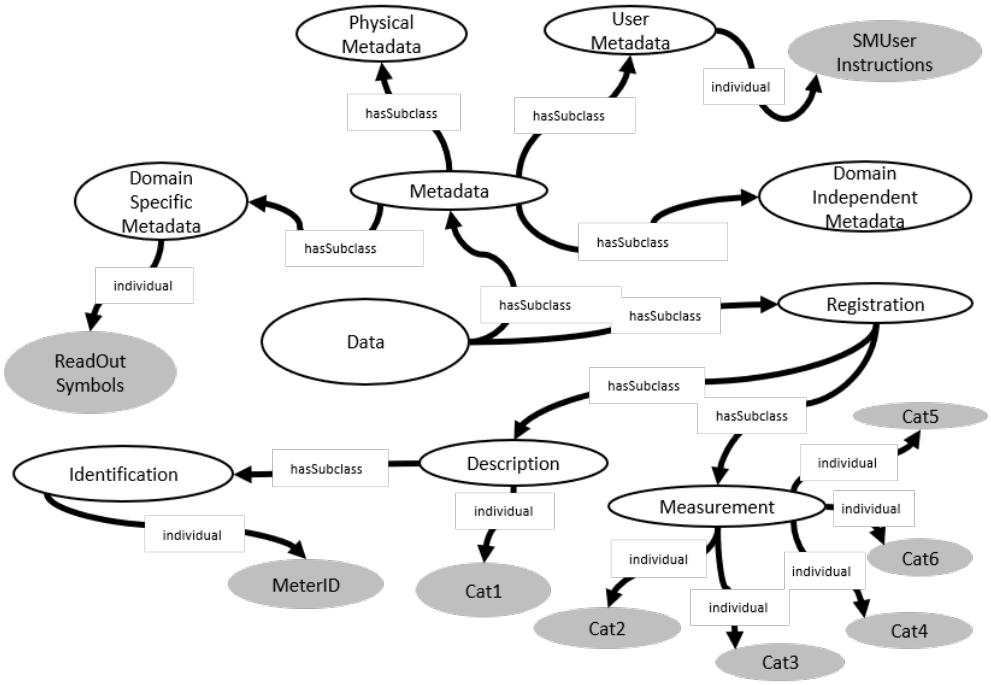


Figure 7-12: The Smart Meter AMDI from a data perspective

In an electricity meter different types of data are stored and transmitted. To be able to clearly distinguish the data, it is divided into 6

categories: 1. Data of interest for the management of the meter; 2. Data of interest for the management of the electricity network; 3. Meter readings of the electricity meter; 4. Meter readings of the gas meter; 5. minute values of the electricity meter + interval data; and 6. Hourly values of the gas meter + interval data. According to a Stedin official, "the network operator is, by law not allowed to receive all of the available meter data". This has been legally determined. However, according to a Stedin official, "in special cases strict agreements about this are made with the end-user", and data needed for the technical management of the meter and the management of the electricity network "may be used by the network operator and read out without permission from the end-user".

### 7.4.2 Components: Technology

The smart meter is a digital meter whose positions are transmitted to the energy supplier and the grid operator. The smart meter measures power consumption, but it also transmits gas meter readings. The smart meter transmits to the energy supplier or network operator at the following moments:

- 1x per year for the preparation of the annual accounts.
- 6x per year for a consumption and cost overview.
- In case of a possible switch to another supplier or relocation.
- If necessary, for management or maintenance of the energy network.

"Smart" refers to the ability of the meter to communicate. This allows meter readings to be transmitted. Stedin can then share this data with energy suppliers. The meter also allows the end-user to return self-generated energy to the grid, without needing an extra meter to measure the generated energy.

In 2015 Stedin started using its own wireless communication network, code-division multiple access (CDMA), although transmission is also still largely done through the General Packet Radio Service (GPRS) standard. According to a Stedin official, "the new wireless communication network forms the basis for further 'upsizing' of the energy grids which can shorten and possibly prevent energy failures". An additional advantage of CDMA is that this network is independent of other networks and Stedin is able to tailor it to meet their current and future standards.

The CDMA network focuses on machine-to-machine data communication. The network is open to various smart grid applications: from sensor to switch, and the data is managed with an internally developed application known as the Meter Front End (MFE). According to a Stedin project manager, "with our central readout system MFE we read

smart meters and provide meter and measurement data to customers and market parties - in the regulated domain … We have radically modified this system, which enables us to handle the increasing traffic flow more efficiently and simply." The CDMA data connection is called the 'P3 port' and the computer server of the network operator where the data is collected is the 'P4 port'. The 'P1 port' is a (telephone) plug connection on the smart meter which is made available to the end-user to be able to connect an energy consumption manager via that connection. The 'P2 port' is the connection between the gas meter and the smart meter. The gas meter itself is not a smart meter, but a modern gas meter is required to allow the smart meter to read and transmit gas consumption. Figure 7-13 below depicts the Smart Meter AMDI from a technology perspective.

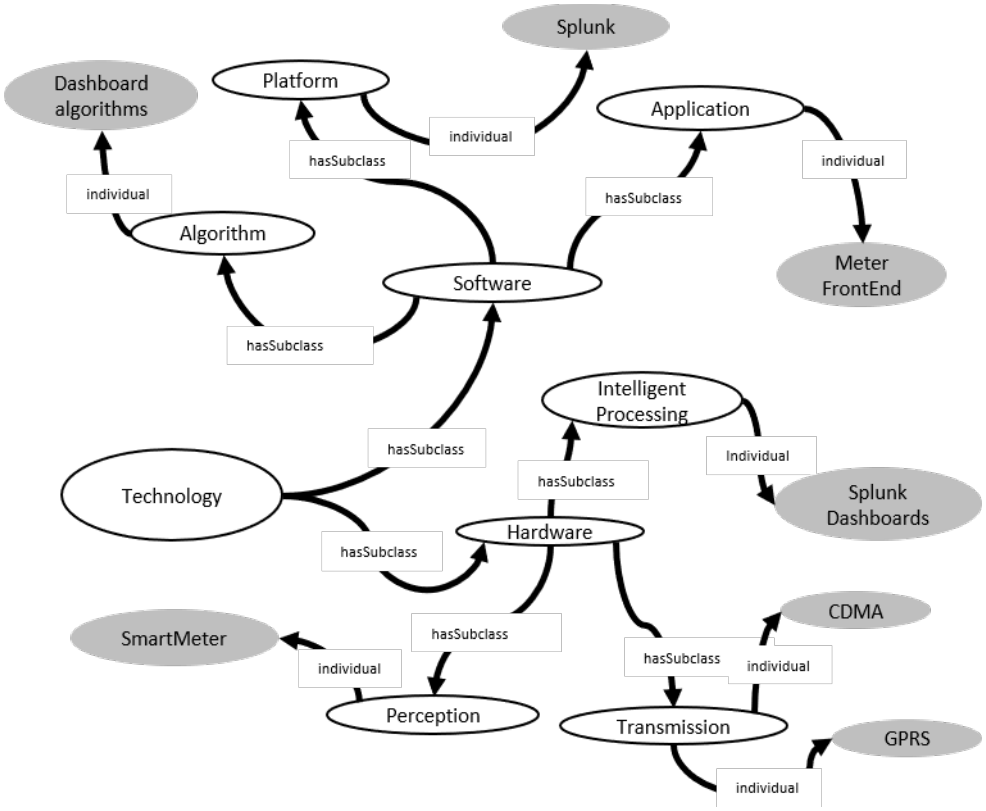


Figure 7-13: The Smart Meter AMDI from a technology perspective

Stedin has recently upgraded their MFE application. According to Stedin, the reason for improving and adapting the Meter Front-End (MFE) system was related to improving efficiency and effectiveness through

predictive analysis. According to a Stedin official, "we expect to use about 600,000 smart meters (electricity and gas) to go to about 4 million smart meters over a period of 5 years, leading to a huge increase in data and meter communication requests and thus to an increasing system load”.

### 7.4.3 Components: Agents

The phasing in of the new smart meter is a large scale operation. Stedin engineers have been installing the new meters according to a phased program. Stedin still receives more than 20 million meter readings from energy suppliers and Independent Service Providers every month on already installed smart meters. But there is a significant increase in data requests via the smart meter. All Dutch citizens have a legal right to a smart meter, but also have the right to refuse the meter. According to the Stedin technicians, “the administrative process of installing smart meters is less error-prone than traditional meters as, in addition to the simplified installation, the barcodes of both meters are also easier to scan”. Stedin has introduced a new sub-organization, the Smart Meter Operations Center (SMOC) in order to gain further insight into the data outage of the smart meter, through the combination of skills from a variety of departments. The SMOC monitors all installed smart meters with dashboards. Stedin has insight into the status of the underlying metering chain processes on a daily basis, which has an impact on the reading of the smart meter. The monitoring also helps to identify outages more quickly, and Stedin is able to respond more proactively to prevent negative customer impact. SMOC involves the Smart Data, Meter Asset Management, Large Scale Connections (GSA), Meter Cabinet & Connections (M&A), IT and Telecom departments. Figure 7-14 overleaf depicts the Smart Meter AMDI from an agent perspective.

Market parties also use meter readings for invoicing and for energy insight, smart allocation and dynamic delivery rates. Meter data is also used for other applications, for example when determining faults in the grid and identifying contract-free connections. This then requires an even higher security of supply and reliability of measurement and metering data. According to a Stedin official, "*we contribute to a sustainable energy transition and cost savings for the end customer. In addition, it is our ambition to be the best grid operator in the Netherlands when it comes to supplying reliable data to market parties … First of all, it is our job to get the highest possible P4 score. The P4 score means reading out the smart meter. We ensure that the right data from the Smart Meter reaches the energy suppliers and independent service providers and they then ensure that the customer gets insight into this. In order to get that P4 score as*

*high as possible, there must therefore be as little as possible a drop in data from the smart meter. That is why we monitor these meters continuously and are quick to act when something goes wrong*."

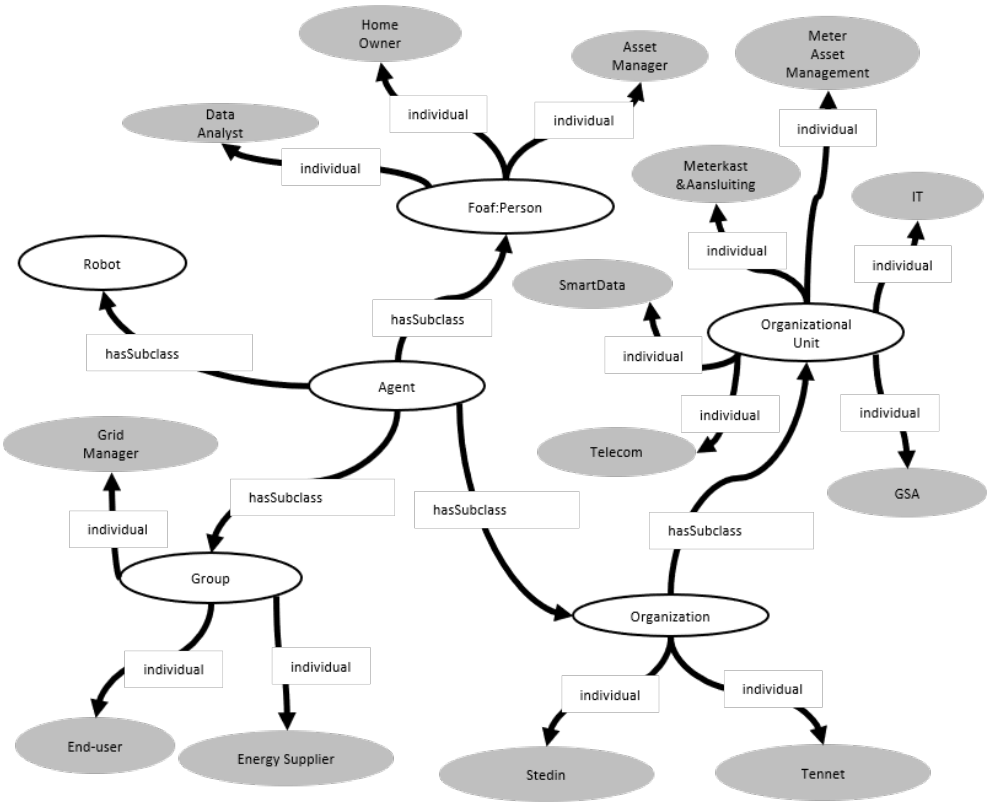


Figure 7-14: The Smart Meter AMDI from an agent perspective

Stedin data analysts are developing innovative data services. Based on many different data, Stedin creates smart combinations that they then use for a variety of purposes. The aggregated data from the smart meter is made available throughout the organization so that Stedin is able to improve process improvements and save costs – attention is given to protecting citizens' privacy rights in accordance with legal requirements. For example, Stedin is developing data applications to reduce faults and malfunctions. A fault can be in the network, but also in the meter cabinet of an end-user. Traditionally, technicians always physically went to the address to assess the situation, but the smart meter now allows Stedin to assess the fault remotely. As such, a Stedin official

suggested that "asset managers need to become more data aware, and data scientists should be intimate with the asset management process".

### 7.4.4 Data Governance

According to a Stedin official, "the end-user owns the data and is able to view information regarding a variety of data transmissions about all types of readings by the network manager". The end-user is able to connect an energy consumption manager to their smart meter to monitor their personal energy consumption. This connection can be done directly, in the form of a device, or indirectly, by giving permission to a third party (independent service provider) to read out their smart meter. Consumption can then be tracked live via an app or on a website. Energy suppliers may view the data from a smart meter only after explicit consent from the end-user. They must report to the service operator that they have this permission before they can access to the end-user's meter readings. Figure 7-15 overleaf depicts the organizational capabilities of the Smart Meter AMDI. In the Netherlands, strict rules apply when it comes to privacy and security. These are laid down in the Personal Data Protection Act and in the Privacy and Security Requirements of Grid Management in the Netherlands. Stedin complies with these laws and regulations. The meter readings that are visible are secured according to regulations. Meter readings are visible to the end-user, the network operator and the energy supplier. No-one else has access to this data, unless the end-user (data owner) expressly consents to this. The smart meter has also been extensively tested and secured against intrusion attempts and hackers. According to a Stedin official, "the security of the smart meter is comparable to that of internet banking". All smart meters meet the legal safety requirements so that unauthorized people cannot access the data.

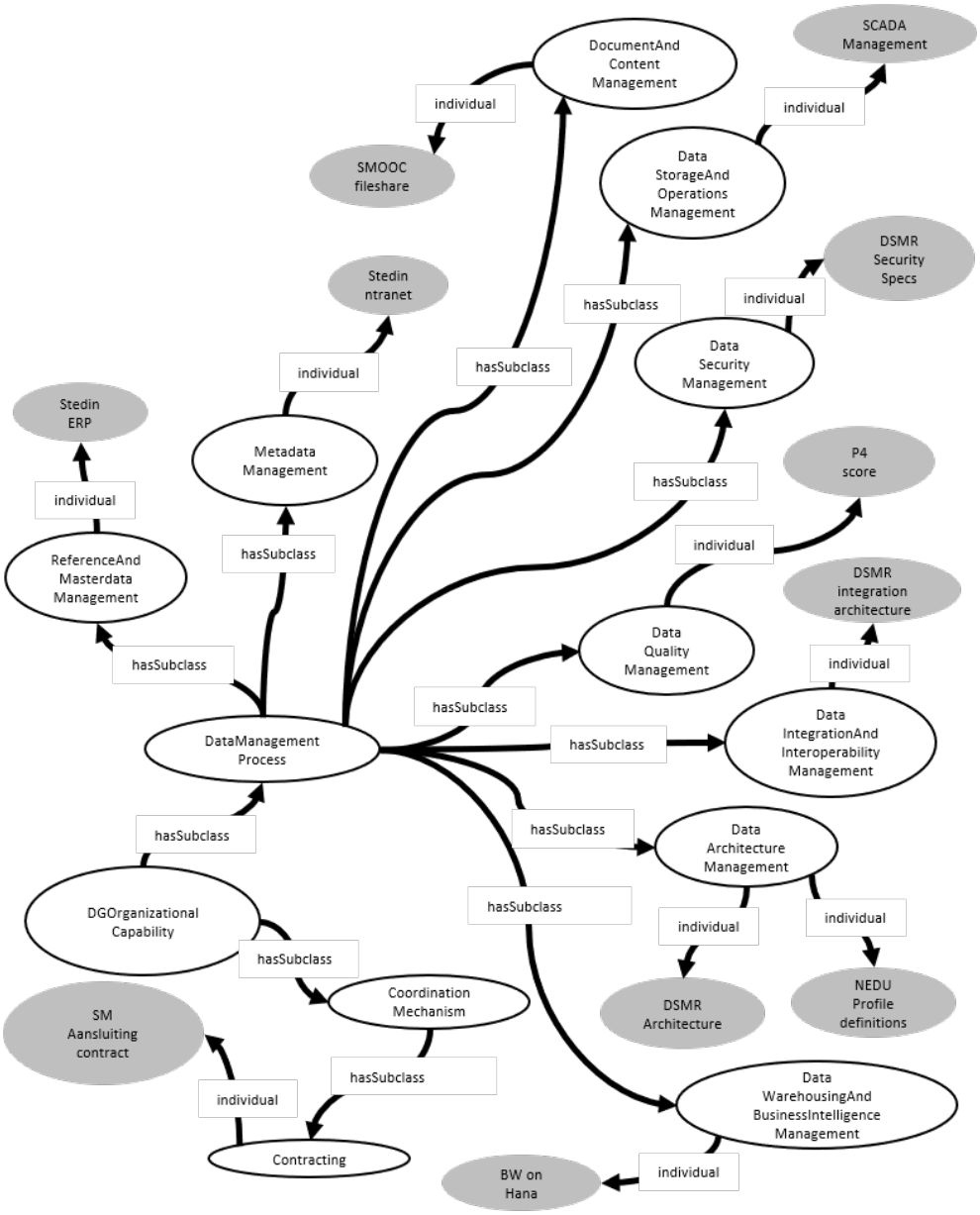


Figure 7-15: Organizational capabilities of Data Governance in the Smart Meter AMDI

Requirements for the Dutch infrastructure for smart meters are specified in the NTA8130 standard and the Dutch Smart Meter Requirements (DSMR) specification. The DSMR was created in a European tender aimed at developing new products and services. Besides all Dutch

Service Operators (united in Netbeheer Nederland), engineering firms and suppliers of measurement systems were also participants in the definition of the requirements. Figure 7-16 below depicts the alignment aspects of the smart meter AMDI.

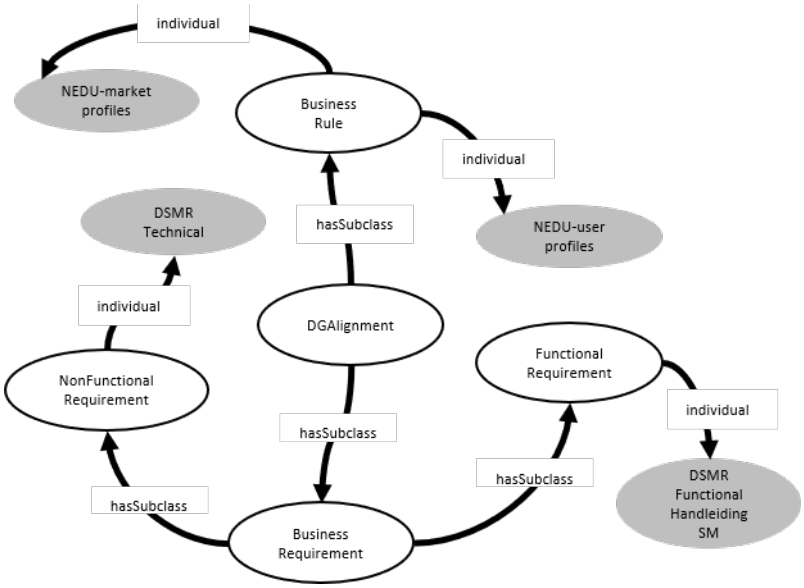


Figure 7-16: Alignment aspect of Data Governance in the Smart Meter AMDI

All the data is stored on the meter itself for a year. Stedin generally receives data with categories 1 to 4. Legal directives suggest that meter data may only be used for the following purposes:

- The annual overview and consumption overviews (6x per year).
- If an end-user switches from energy supplier or relocates.
- The maintenance of the energy network.

A Stedin official admitted that "it is very tempting to use large data techniques to link large datasets to each other and to search for correlations", but they also underlined the importance of "well thought-out policies that working with privacy-sensitive data requires". For the Stedin official it is important to be able to clearly demonstrate that "you have a goal with the data you use". For every use case on the Data Lake, Stedin carries out a so-called privacy impact assessment (PIA). Stedin is constantly looking for the balance between shielding data and equipping colleagues with the right data. This is because analyzing data is not only reserved for data scientists of the CDO office. Analysts throughout the organization may be given access to the data lake where necessary. Stedin has a data analytics community where colleagues from different

business units come together to discuss how they can help each other with data and analysis. Figure 7-17 below depicts the clarification aspects of the smart meter AMDI.

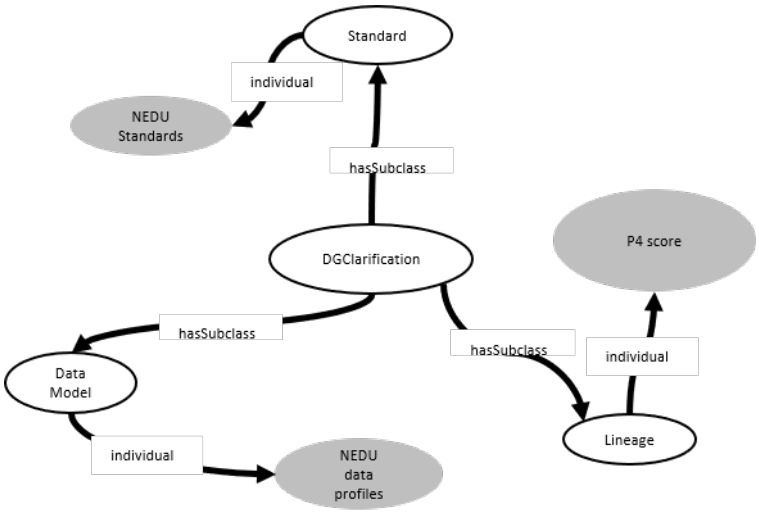


Figure 7-17: Clarification aspects of Data Governance in the Smart Meter AMDI

Net managers in The Netherlands must adhere to a code of conduct when processing personal data. This is supervised by the Authority for Consumers and Markets and the Dutch Data Protection Authority. There has been a lot of discussion about the privacy aspects of the smart meter in The Netherlands. When the meter transmits data, usage data becomes available to parties other than the end-user who has been identified as the owner of the data. The data connection with the smart meter itself has been subjected to hack-sensitivity testing by the Digital Security section of the Radboud University. These tests showed that the connection is well secured. The Consumers' Association does, however, call for a clear code of conduct for network operators, energy suppliers and PES (independent service providers, for example the provider of a consumption manager). At the moment, different codes of conduct apply to different parties. For example, according to a Stedin official, “it is not always easy to find out who can view data from the smart meter under which conditions”. Figure 7-18 below depicts the compliance aspects of the smart meter AMDI.

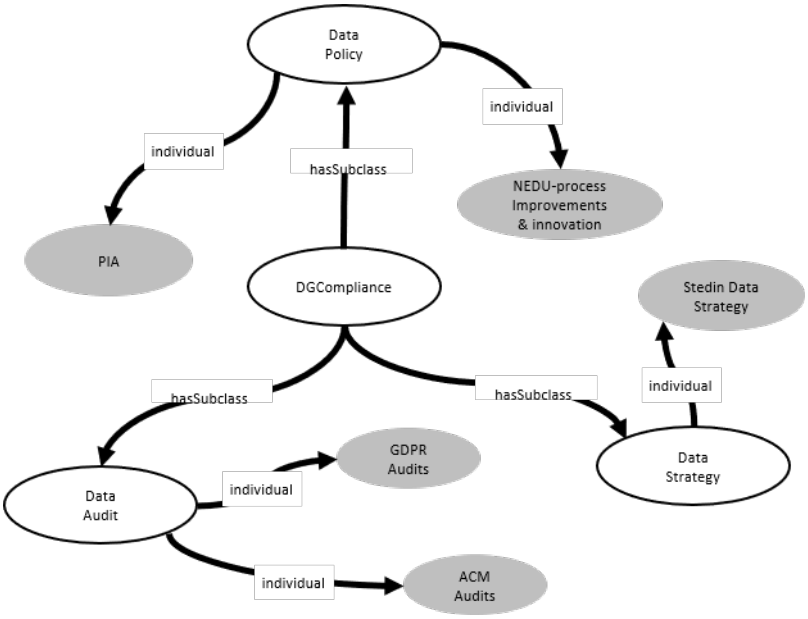


Figure 7-18: Compliance aspects of Data Governance in the Smart Meter AMDI

Due to past fraudulent activities, Stedin performs careful controls of whether the service providers have checked the identity of the applicant, so that an end-user's identity is not misused. However, it is still recommended by Stedin officials that end-users "perform their own controls of the companies involved in managing energy consumption data on a third party basis and how the company treats the data".

### 7.4.5 Environments

Stedin has begun an information point in the Ommoord district in Rotterdam due to the number of complaints that came in during the offer of the smart meter in this district. In this regards, personal contact with the residents has proved necessary. Stedin sees the information point as a test case to investigate whether an information point is a channel that they would want to use more often during the large-scale offer of the smart meter (GSA). The information point, near a busy shopping center, is staffed by external hosts six days a week. They have received training from colleagues from the department GSA and Meter and Connection and are well versed in the capabilities and functionality of the smart meter. The information point staff are supervised by colleagues from GSA, Meterkast and Connection, Front Office, Supplier Desk and Smart Data. With the sharp increase in the number of customers with smart meters,

Stedin expects data traffic to increase substantially in the coming years. Figure 7-19 below depicts the Smart Meter AMDI from an environmental perspective.

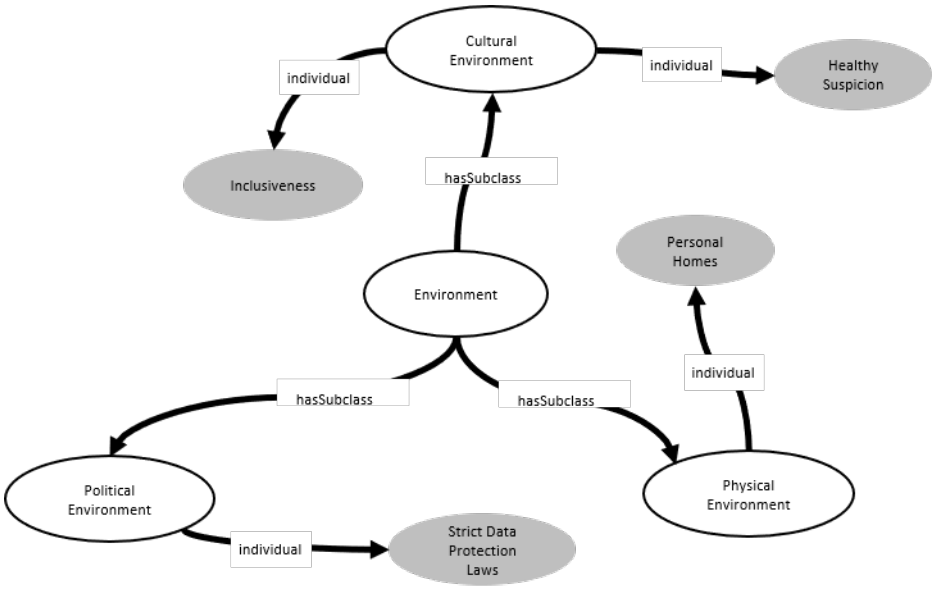


Figure 7-19: Environmental aspects of the Smart Meter AMDI

In order to minimize complications in the market processes due to de-regulation, a Stedin official indicated that "components have been implemented in phases via regular sector releases".

## 7.5 Smart Energy Grid Hoog Dalem: Stedin

Our third test case, case 6 - Hoog Dalem Smart Energy, is also managed by the Stedin Group. 32 households are participating in the smart energy system test in the All-Electric district of Hoog Dalem in Gorinchem. Hoog Dalem is a residential area within the Dutch city of Gorinchem in South Holland. The Hoog Dalem residential area is interesting due to the large number of the houses that have been fitted with solar panels, meaning that the residents are less dependent on electricity from the national and regional grids. It is therefore an all-electric area, and, unusually for the Netherlands, there is no gas network. A number of houses are also fitted with a battery system for electrical storage. Furthermore, every house in the district is heated by a heat pump. The Hoog Dalem project makes use of the Universal Smart Energy Framework (USEF). Figure 7-20 below depicts an overview map of the area of the Hoog Dalem area.


Figure 7-20: A map of the Hoog Dalem area (www.google.com/maps accessed: 2018)

The heat pumps and the return of self-generated electricity means a greater demand for capacity from the electricity network. In fact, according to a Stedin official, "bottlenecks may occur in the regional grid when a whole district implements solar paneling". To avoid this, service operators require innovate methods to capture renewable energy flows, as installing more or heavier power cables is considered an expensive and inefficient solution. As such, it is important to investigate other possibilities such as electricity storage and the efficient coordination of supply and demand made possible through IoT. Many of the Hoog Dalem residents have solar panels, a battery, and a measuring and control system in the meter cabinet as well as access to a web interface. With this web interface residents have insight into their data, and the energy usage of household objects such as, for example, the dishwasher, fridge or washing machine. Figure 7-21 below depicts the IoT system in relation to a specific household.

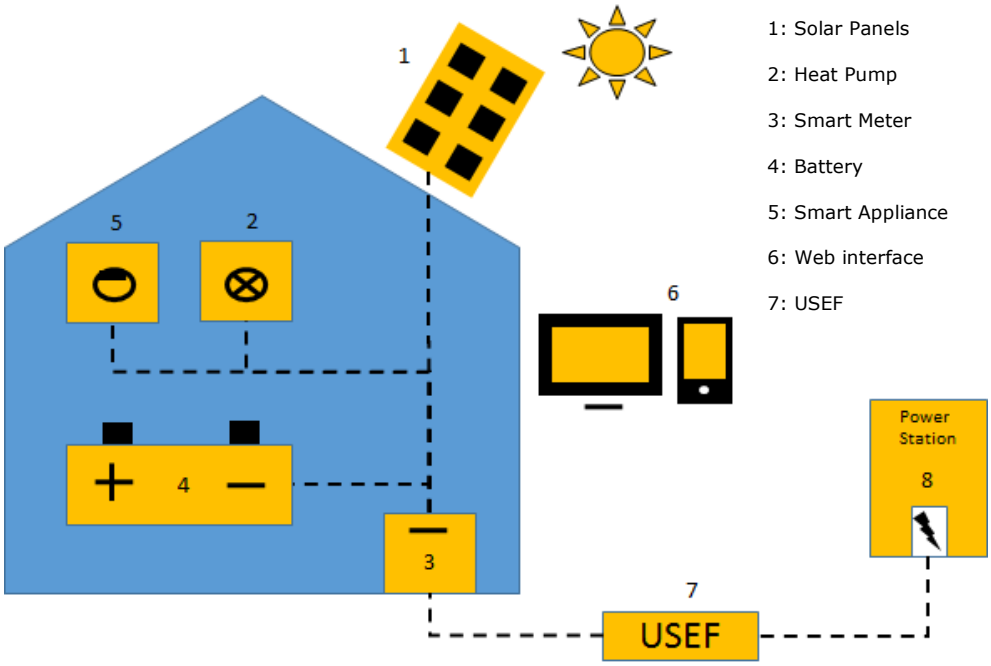


Figure 7-21: The Hoog Dalem Smart In-Home Energy System (Adapted from: "Eindrapport Hoog Dalem DEF")

The smart in-home system mentioned above is connected via a gateway to a separate IT environment. The market roles have been implemented in a single ICT environment, to reduce costs and to avoid possible connectivity issues regarding data traffic between different environments.

### 7.5.1 Components: Data

The smart in-home energy system includes all the measurement points required to maintain the system. The system ensures that it is possible to program the smart appliances to work during daylight hours when energy is available from the solar panels, however, the focus lies with the impact on the stored energy in the batteries. Figure 7-22 below depicts the AMDI model extended and personalized to include class "individuals" used in the Hoog Dalem case.

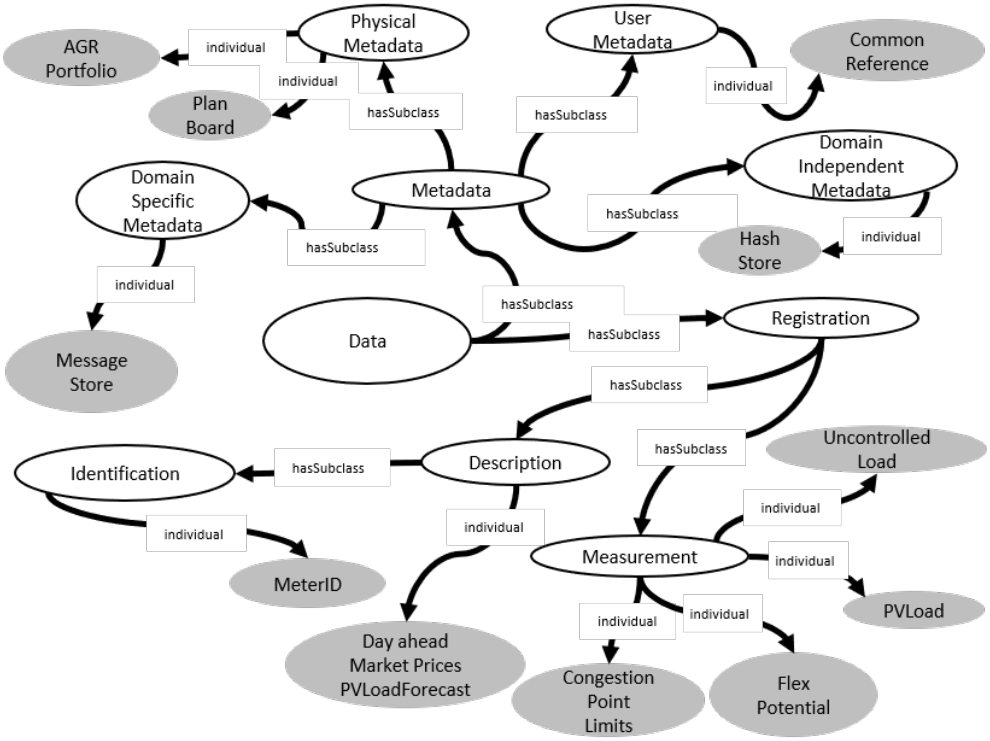


Figure 7-22: The Hoog Dalem AMDI model from a data perspective

Measurement points in the Hoog Dalem IoT system include:

- Electricity exchange with the grid
- Use of the heat pump
- Electricity use of smart appliances
- Electricity production of the solar panels
- Electricity exchange, charge and discharge of the batteries

Congestion points have limited capacity for transporting electricity and when these values are exceeded the Grid Safety Analysis 'fails'. The UncontrolledLoad is defined for the (virtual) congestion point, being the transformer all houses are connected to. Virtual, because the actual capacity is substantially more than the capacity configured. In addition, other houses are connected to the same transformer, but these are ignored. It contains a forecast for the next day of average power in 15 minute time steps. The production limit is the maximum net production (PVLoad-UncontrolledLoad) that will occur at the congestion point. This also is a forecast of average power in 15 minutes time steps.

### 7.5.2 Components: Technology

As seen in Figure 7-23 below, the reference implementation contains software packages for the market rolls in the form of pluggable business components (PBCs). At Hoog Dalem, the market roles are implemented in a single ICT environment, according to a Stedin official, "to reduce costs and avoid possible communication issues with regards to the data traffic between different environments".

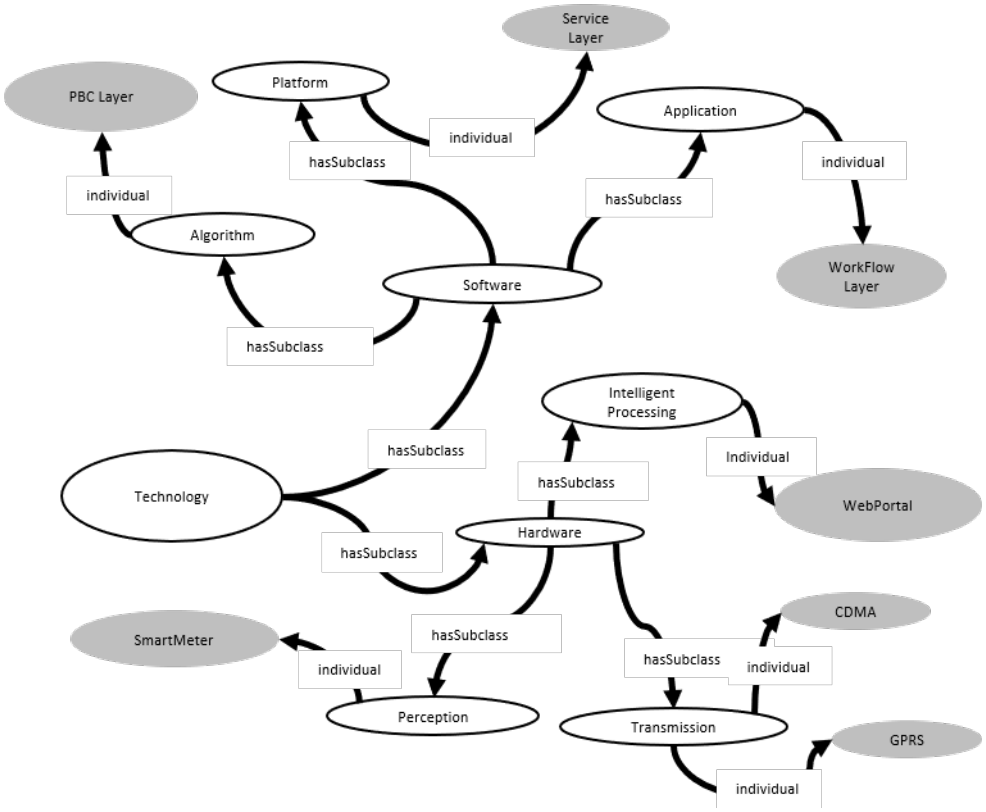


Figure 7-23: The Hoog Dalem AMDI model from a technology perspective

At Hoog Dalem, the general pluggable business components (PCBs) were replaced by components that fit within the desired functionalities of the project. The PCB layer enables a third party to plug in custom business logic in a workflow process step. The workflow layer provides an implementation of the processes and business services, specifically the processes defined by the market-based coordination mechanism (MCM). The service layer provides the operational data stores

required to realize the application components, such as a reliable set of communication capabilities, and logging and monitoring.

Electricity meters register the electricity consumption used as well as the returned electricity. The meters automatically report the meter readings. With regards to transmission, the Hoog Dalem case uses General Packet Radio Service (GPRS), a packet oriented mobile data service on the global system for mobile communications (GSM). The reference implementation is delivered with a component that delivers data for PBCs, currently for demo purposes only. This component is the PBC Feeder that delivers the required input data for separate PBC implementations.

### 7.5.3 Components: Agents

The Hoog Dalem Energy Project was carried out by Stedin with a number of partners. 32 households also took part in the case as a practical research into a future energy system. Figure 7-24 below outlines the main stakeholders and agents taking part in this case study.

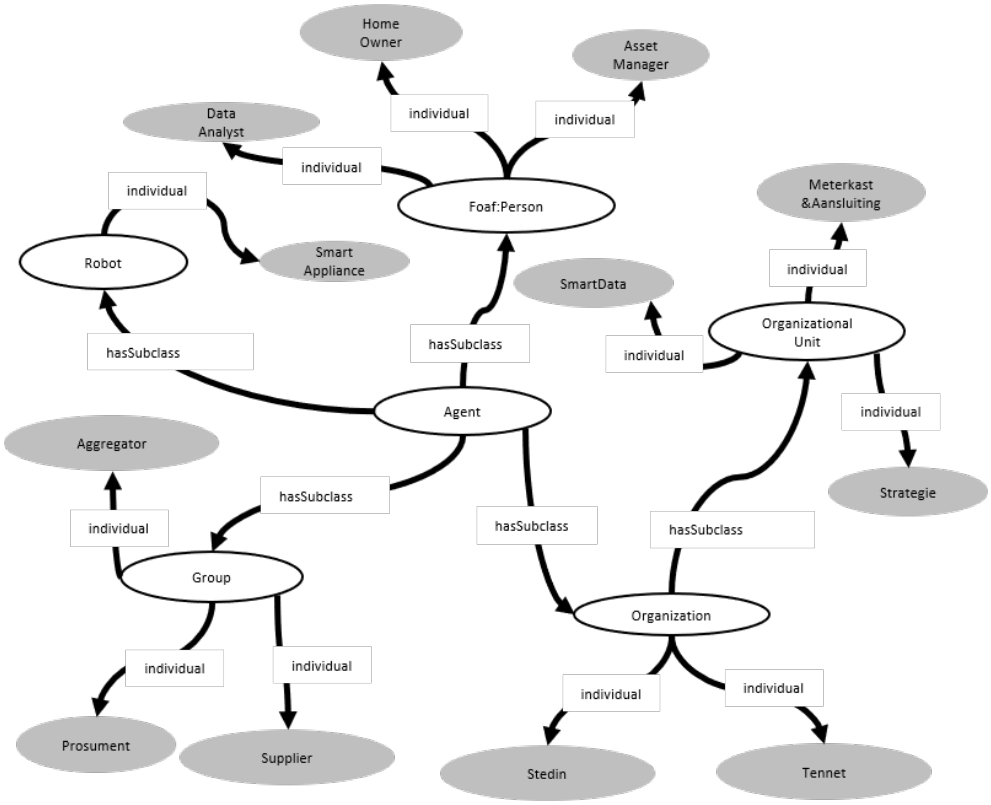

Figure 7-24: The Hoog Dalem IoT AMDI model from an agent perspective

The Hoog Dalem case includes 3 main groups of agents which include the prosumer, the aggregator and the DSO. The prosumer is an end-user of energy who also produces energy. In this case, the household owner, and as such, the group, "prosumer", is made up of the individual households. The aggregator is a new role in the energy distribution system in The Netherlands and is defined as an organization that bundles the energy supply services. All new roles used in the Hoog Dalem pilot project were filled in by the consortium partners. Other important organizations in the supplier category are the Balance Responsible Parties (BRP) and the Transmission System Operator (TSO). BRPs provide their E-programs the day before, the TSO checks whether or not the E-programs are correct. The measuring is performed by the DSO.

### 7.5.4 Data Governance

Hoog Dalem follows the USEF specification, with special regards to the framework specifications. According to a Stedin official, "USEF defines individual roles and responsibilities, how agents should interact, and how they can benefit by doing so". Figure 7-25 below depicts the organizational aspects of data governance in the Hoog Dalem AMDI. As seen in Figure 7-25, various coordination mechanisms are defined within the framework. The MCM is designed to optimize the market in time, capacity and power. From a more technical perspective, the messaging system works on a contract-based approach, using a point-to-point integration between the different actors exchanging messages between each other as well as a synchronous message exchange mechanism. The performed validations are shown in the common inbound message flow sequence diagram. The results of these validations are returned to the sender. The synchronous message exchange is realized by using REST over https. Hoog Dalem have also adopted further data management processes as outlined in the USEF documentation. For example, the data architecture and data management guidelines are described in the system architecture and privacy and security guidelines documents. The reader should note that only example individuals are presented in Figure 7-25 due to space constraints.

Stakeholder requirements of the Hoog Dalem AMDI are outlined in use cases. The Market-based Coordination Mechanism (MCM) defines how the different stakeholders active in the MCM should behave and interact. However, according to a Stedin official, "it was discovered that not all relevant aspects are specified by USEF. An example of this is that USEF

does not specify how an aggregator optimizes its portfolio or how an aggregator determines how much flexibility is available where and when".

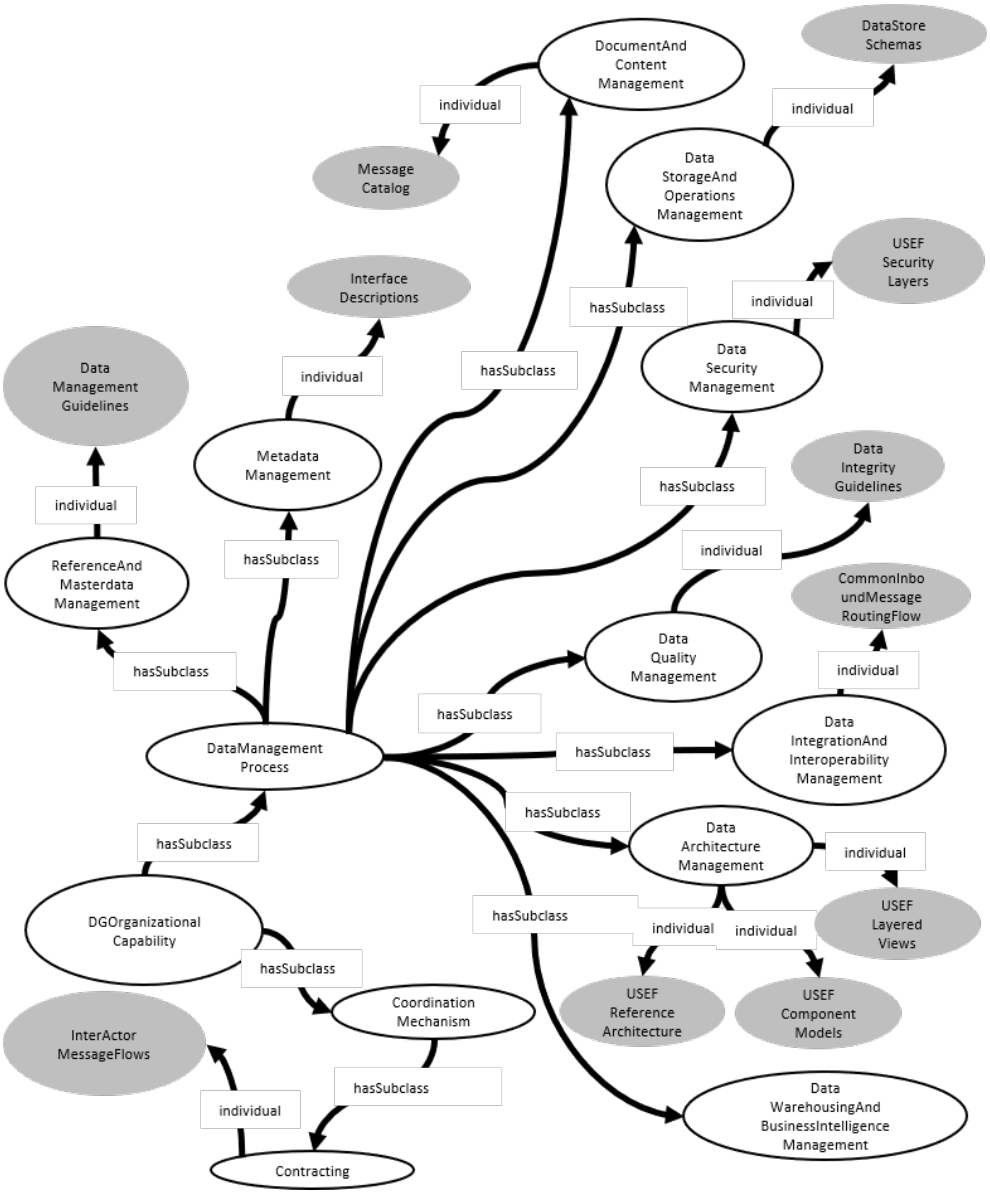


Figure 7-25: Organizational capability aspects of data governance in the Hoog Dalem AMDI.

Figure 7-26 below depicts the main alignment individuals in the Hoog Dalem AMDI.

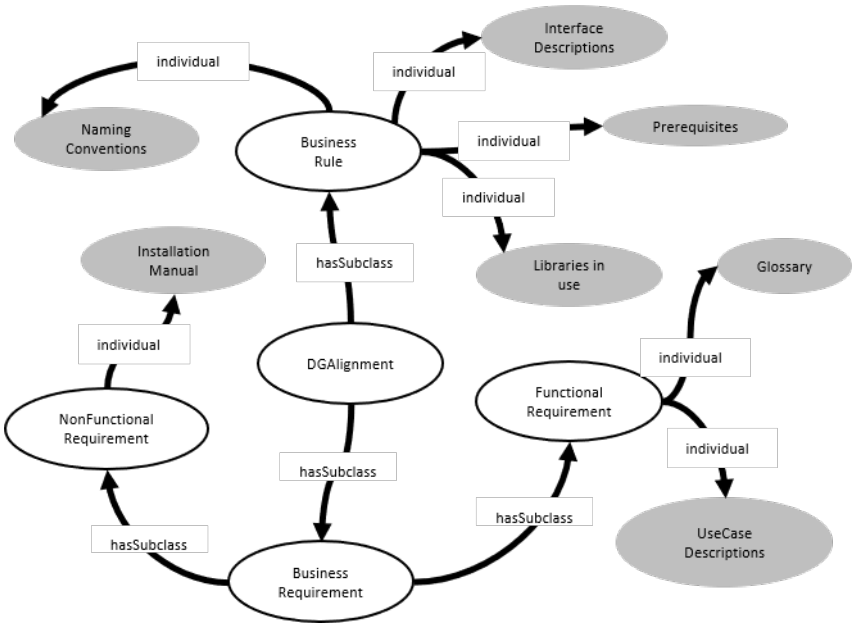


Figure 7-26: Alignment aspects of data governance in the Hoog Dalem AMDI

Functional requirements are outlined in the USEF Implementation Guidelines. Behavioral requirements are outlined in the Installation Manual of the USEF Framework. These behavioral requirements include prerequisites, instructions for starting and stopping the USEF environment, configuration guidelines, guidelines for resolving participant information, and guidelines for uploading data. Similarly, a wide variety of business rules, including which libraries are in use, naming conventions, as well as glossaries and definitions have been adopted from the USEF specifications. Figure 7-27 overleaf depicts the clarification aspects of data governance in the Hoog Dalem IoT AMDI.

Similarly to the alignment aspects of data governance, the Hoog Dalem project largely adopts clarification aspects as outlined in the USEF Framework specifications, and the USEF Implementation guidelines. For example, the data models are outlined in detail in the Framework Specifications (Message Transport and Descriptions). Messages consist of XML, use UTF-8 encoding, and are validated against the schema corresponding to the specification version implemented by a participant. Message types can be differentiated using the name of their root node.

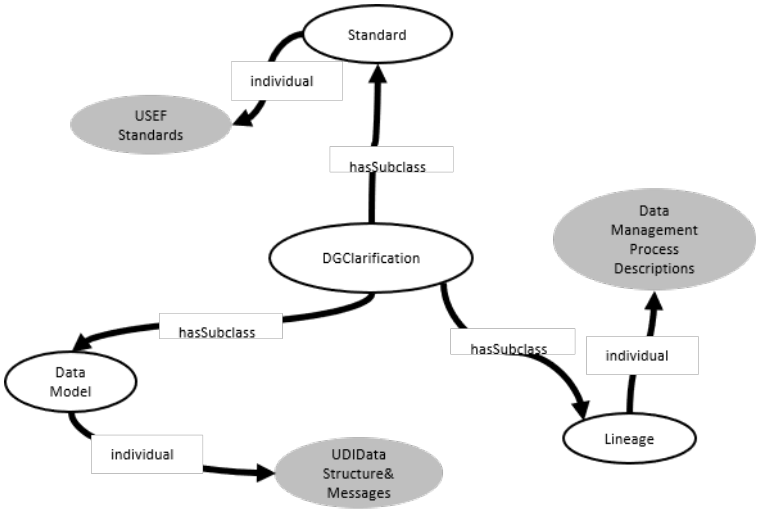


Figure 7-27: Clarification aspects of data governance in the Hoog Dalem AMDI

There are three levels of compliance used by Hoog Dalem: 1. protocol, 2. process, and 3. service compliance. Protocol compliance deals with the syntax and semantics of messages. Process compliance considers the processes in and interactions amongst the roles. Finally, service compliance deals with the validation whether a service provider is capable of providing the flexibility service according to the contractual arrangements.

In the Hoog Dalem project, protection of privacy & security is viewed as an ongoing task. According to a Stedin official, "privacy measures will need to evolve over time in order to deal with changing societal trends, whereas security measures will need to evolve over time in order to mitigate increasingly sophisticated hacking techniques". Figure 7-28 below depicts the compliance aspects of data governance in the Hoog Dalem AMDI.

### 7.5.5 Environments

The Hoog Dalem area offers a high standard of living. The area has access to necessary amenities such as shops, schools and care. Hoog Dalem can be described as spacious living amidst greenery and water in the atmosphere of the Dutch Waterline with child-friendly, safe neighborhoods and with nearby facilities. Hoog Dalem consists of four sub-areas: De Donken (which has already been largely built), Center Hoog Dalem, Het Lint and De Eilanden. Each area has its own informal culture and has a different type of housing. Hoog Dalem as a residential area is

still under construction, but when completely finished, will have about 1,400 homes and a shopping center.

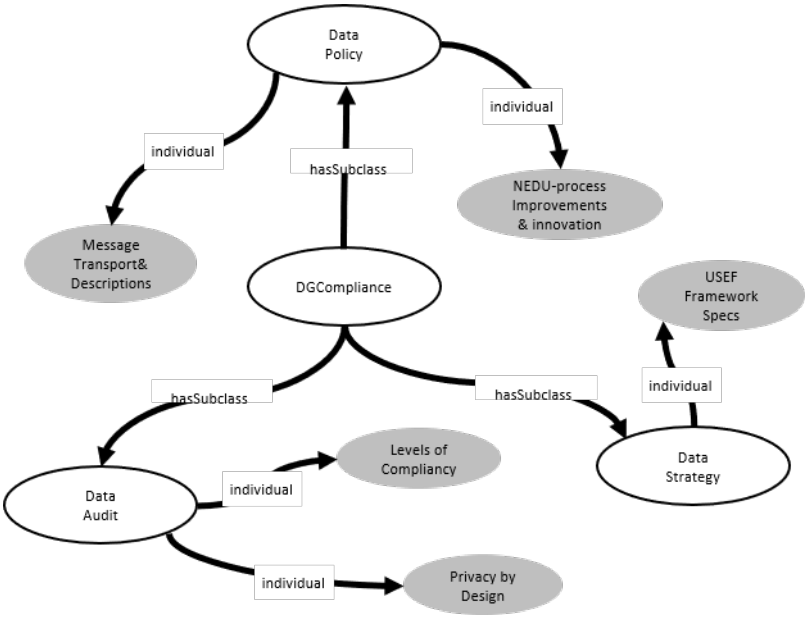


Figure 7-28: Compliance aspects of data governance in the Hoog Dalem AMDI.

The demographics of the area (https://www.parlement.com based on figures from the Central Bureau of Statistics) suggest that the area has a lower than average number of residents per square meter than the rest of the Netherlands, with a high proportion of professionals between the ages of 45 and 65 and a high proportion of teenagers. It is a residential area with established families with higher incomes. http://www.buuurt.nl (based on figures from the Central Bureau of Statistics) suggests that the average house price in Hoog Dalem is around €500.000.- which is higher than average in the Netherlands. According to http://www.buuurt.nl, the political preference of residents in the area is that of conservative-liberal parties, with an obvious preference for business focused parties such as the Volkspartij voor Vrijheid en Democratie (VVD). According to research conducted by Stedin in the area (Hoog Dalem report: "Eindrapport Hoog Dalem DEF"), there is clearly a dominant segment in the Hoog Dalem district in which more than 95% of the residents of the district attach great value to a pleasant living environment and a house in which superior comfort is provided. Technology plays an important part in this role. Figure 7-29 below depicts the environments in which the Hoog Dalem IoT AMDI is located.

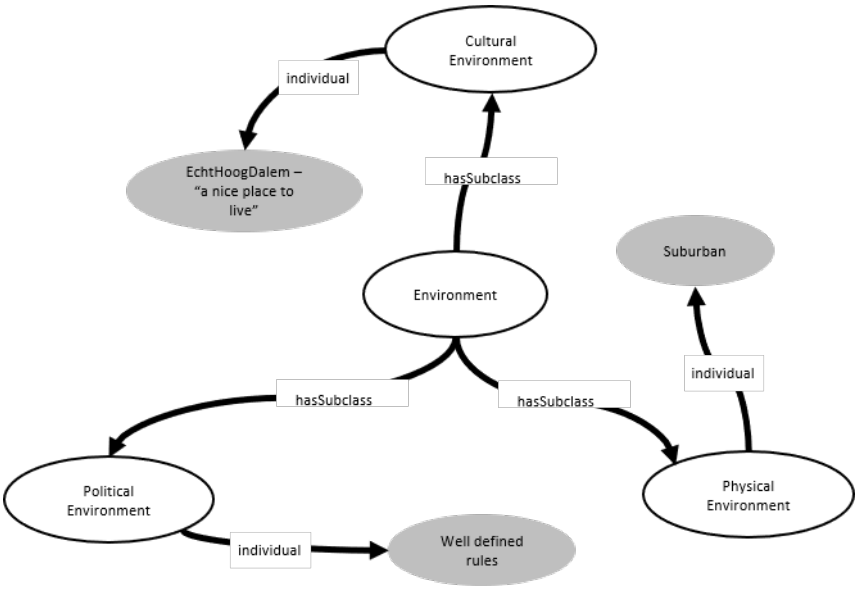


Figure 7-29: Environments in the Hoog Dalem AMDI.

According to Stedin, "this group strongly believes that technology makes life easier or more comfortable". According to Stedin, "this group makes up an average of 23% of the total Dutch population, demonstrating a large disproportion for Hoog Dalem". Stedin suggests that "this extreme can partly be due to the fact that the neighborhood is new and that there is still little data available". Another possible explanation provided by Stedin is that "the district contains many relatively large and expensive houses, with an innovative heating system". Stedin believes that such houses "may attract residents who are interested in technology and that for, these people, comfort may more be important than cost".

## 7.6 Discussion

This section discusses the results of the test case studies. The goal of the test case studies was to test the usability of the AMDI model for improving understanding of asset management though IoT. As such we first discuss the validation of the test case studies themselves for their appropriateness with regards to the generalization of the research. The test case studies are therefore validated in section 7.6.1 against the criteria for case selection (see Table 2-1). After discussing the validation of the case studies, we discuss the usability of the model against the criteria for model validation in section 7.6.2. Finally we discuss the results

of the tests of the design propositions with regards to the usefulness of the model.

### 7.6.1 Test 1: Validation of the Test Case Studies

Table 7-5 below shows how the case studies are validated. The table compares the case studies to the case study criteria discussed in Chapter 2.

Table 7-5: Validation of the Test Case Studies.

| Criteria | Case Studies | | |
|---|---|---|---|
| 1. The case must occur within a distinct organization. | Case: WIM<br>Org.: RWS | Case: Smart Meters<br>Org.: Stedin | Case: Hoog Dalem<br>Org.: Stedin |
| 2. The primary processes of the organization must be focused on the management of significant infrastructure. | Road management (national highways):<br>IoT system used to determine overloading of vehicles which has a direct influence on distresses in porous asphalt including rutting, raveling and reduced skid resistance | Grid management of middle tension electrical grids:<br>IoT system used to determine capacity and breakages in the middle tension electrical grid | Grid management of low tension electrical grids:<br>IoT system used to determine capacity and breakages in the low tension electrical grid |
| 3. The case environment should be "data-rich". This means that the organization should produce, manage and maintain at least 5 large datasets as well as a more than twenty small to medium data sets which support the asset management process. | RWS has more than 1000 datasets, including large datasets such as large scale topography base registration as well as many large datasets such as the National Road Data (NWB) | Stedin has more than twenty large datasets, including large datasets such as the asset data related to the gas and electricity networks and data generated by the smart meters themselves | Stedin has more than twenty large datasets, including large datasets such as the asset data related to the gas and electricity networks and data generated by the smart meters themselves |

| Criteria | Case Studies | | |
|---|---|---|---|
| 4. The AMDI must include at least one example of IoT adoption. | *Number of stations*: >15<br><br>*Type of services*: Collaborative aware services<br><br>*Age of System:* >18 years<br><br>*Type of sensors:* See figure<br><br>*Data transmission:* VICNet (cable) | *Number of stations*: >500 000<br><br>*Type of services*: Information aggregation services<br><br>*Age of System:* >4 years<br><br>*Type of sensors:* Electricity meter<br><br>*Data transmission: GPRS, CDMA (wireless)* | *Number of stations*: >20<br><br>*Type of services*: Collaborative aware services<br><br>*Age of System:* >4 years<br><br>*Type of sensors:* Electricity meter<br><br>*Data transmission: GPRS (wireless)* |
| 5. The case should occur within The Netherlands. | Case encompasses the national highways of the Netherlands and is managed by central government | Case encompasses the electrical grid of the regions of South Holland and Utrecht in the Netherlands | Case encompasses the electrical grid of a neighborhood in Gorinchem, a city in the Netherlands |
| 6. The organization should be of type government or semi-government (majority shareholders should be government). | Type: Central Government<br><br>Stakeholders: Asset Managers, General public, Industry, Municipalities, Provinces | Type: Semi-Government (majority shareholders are municipalities)<br><br>Stakeholders: Asset Managers, General public, Private asset owners, Industry, Agriculture, Municipalities, | Type: Semi-Government (majority shareholders are municipalities)<br><br>Stakeholders: Asset Managers, General public, Private asset owners, Municipalities, |
| 7. Cases should occur at varying geographic coverage levels. | Level: National | Level: Regional | Level: Local |
| 8. Cases should occur in varying asset management domains. | Road management: National Highways | Mid-tension electrical grid management | Low tension electrical grid management |

| Criteria | Case Studies | | |
|---|---|---|---|
| 9. The organization must be willing to cooperate with researchers and must be willing to provide access to the information required for the research. | RWS provided full access to the researchers– see table 7-1 | Stedin provided full access to the researchers– see table 7-2 | Stedin provided full access to the researchers– see table 7-3 |

Table 7-5 above demonstrates that the case studies comply with the criteria as specified in Chapter 2. Furthermore, the data was collected according to the case study protocol and was stored in the case study database as per the suggestions made by Yin (2009) which established a chain of evidence. The data included multiple sources of evidence (see tables 7-1, 7-2 and 7-3). In order to guard against investigator bias, interviews were conducted by several different interviewers. The results were then discussed within the group and with other colleagues, and key informants from the various organizations were given the opportunity to review the draft case study report. In light of these arguments we argue that the results of the case studies, as discussed in the sections below, may be considered to be reliable and valid within the research domain.

### 7.6.2 Test 2: Usability of the AMDI Model

Due to privacy concerns we do not refer to the specific cases or persons in the following sections.

Criteria 1 and criteria 2 for interpreting the findings are aimed at determining the construct validity of the model itself. Is the model overcomplicated or, conversely, incomplete? Appendix C shows that individuals for most of the object classes could be found in all three of the test cases. Important exceptions include physical and domain specific metadata. Thorough discussions with subject matter experts in the test cases as well as discussions with colleague researchers were unable to determine extraneous object classes at the secondary level of the model. As such, we believe that the model is compliant with criteria 1 and 2 and that the model is valid for the test cases. It is worth noting, however, that in some object classes further classification at lower levels is potentially possible. An example of this lies with the business rules. It is potentially possible to further classify different types of business rules such as constraints, derivations, facts and definitions. We did not include this level of classification in the model as none of the case studies (exploratory or

test) provided evidence in which examples of all of these classifications could be found. Although many interviewees assured us that individual business rules were of paramount importance, with especial regard to definitions of data, it would appear that a highly disciplined documentation of business rules as suggested by Feldstein & Glasgow (2008) is not necessarily of major influence on asset management through IoT. In asset management, the teams dealing with the data are often small with a core of highly skilled subject matter experts who are familiar with the data. This may also be the reason that some metadata individuals were unable to be discovered by the research team. As such, the business rule insight suggests that people factors such as awareness and levels of knowledge and skill (Aarons et al., 2011; Graham & Logan, 2004) may have a larger influence on IoT adoption in asset management than other factors.

Criteria 3 suggests that the user should be able to complete the model for specific situations within the time limits of a two hour workshop. A major barrier to achieving this criteria was the availability of experts with an all-encompassing view of the case. The AMDI model has a broad scope, which means that very few people are able to work with the model in its entirety alone. This is also one of the strengths of the model in that it brings people from different subject areas together to discuss and view the infrastructure from different perspectives. However, achieving the situation whereby all required individuals were in one room at the same time was challenging. We therefore made the decision to work with smaller groups on sections of the model as opposed to working with a larger group in one sitting. Working with individuals or smaller groups in time periods of one hour, we gathered enough data to complete the model in the allotted time period. The completed models were then confirmed by all the participants through the contact person. The fact that the models were completed in multiple sittings should be taken into account when considering the results due to the potential for incorrect interpretations and bias. The total time taken to complete the model was monitored to a precision of 15 minutes.

Criteria 4 suggests that the model should be reasonably easy to use, in that the model should be relatively self-explanatory. As such, the researcher allocated 15 minutes per session to the explanation of the model and the required actions of the participants. Check questions were asked as to whether or not the participant understood how the model worked and what was required of them. The model was presented to the users by means of a whiteboard, or as a digital print version of the model as a presentation. The participants were then asked to verify the model by verifying the identified individuals. Using the results of the

interviews/workshops, the researcher then formally completed the model in Protégé and confirmed the findings with the contact persons. None of the participants reported difficulties in understanding the model or what was required of them, but some explanation was required as to the definition of an "individual". Differing interpretations of what an individual is led to slight differences in levels of detail between the case studies.

Criteria 5 suggests that the participants should feel positively about using the model. In other words, users should feel comfortable using the model and should want to use it. The response to the model by the participants was, in general, positive. This feeling of positivity was expressed in a number of ways during the test cases. For example, with regards to learning, one participant who works in a senior advisory role suggested that they had "*learned new things about their own system*" from the model. Other participants responded that the model provided an overview, and "*gave them a helicopter view of the system*" which helped to understand how the parts of the system which they were working with were connected to products and services performed by other departments. With regards to the use of the model for planning purposes, participants suggested that the model was a "*handy planning tool*" which project managers could use to reduce the risk that critical actions were missed and to map out a workable roadmap. Less positive remarks included feedback that it was sometimes difficult to include individuals in the model, as although the respondents acknowledged that the individuals were important, they were not immediately certain as to the exact individuals for their case. The participants suggested that this was not the fault of the model, but of the maturity of the system under study.

Table 7-6: Summary of the results of Test 2: the usability of the model

| **Criteria** | **Results of the Test Case Studies** | | |
|---|---|---|---|
| | **RWS: WIM** | **Stedin: Smart Meters** | **Stedin Hoog Dalem** |
| 1. Individuals for each object class should be present in the case. | All classes were populated with individuals. | All classes were populated with individuals. | All classes were populated with individuals. |
| 2. All individuals present in the class should logically fit into an object class in the model. | No extraneous individuals were discovered. | No extraneous individuals were discovered. | No extraneous individuals were discovered. |

| Criteria | Results of the Test Case Studies | | |
|---|---|---|---|
| | **RWS: WIM** | **Stedin: Smart Meters** | **Stedin Hoog Dalem** |
| 3. The user should be able to read and understand the entire model within the time limits of a two hour workshop. | 2 rounds of interviews/workshops were required to complete the model. Interviews lasted 1 hr. Total average time per group: <2 hours | 2 rounds of interviews/worksho ps were required to complete the model. Interviews lasted <1 hr. Total average time per group: 1.5 hours | 2 rounds of interviews/worksho ps were required to complete the model. Interviews lasted 1 hrs. Total average time per group:2 hours |
| 4. The user should be able to work with the model after a short explanation lasting no more than 15 minutes. | Users reported no difficulties in understanding how the model should be completed. Some explanation was required with regards to the interpretation of an individual. | Users reported no difficulties in understanding how the model should be completed. Some explanation was required with regards to the interpretation of an individual. | Users reported no difficulties in understanding how the model should be completed. Some explanation was required with regards to the interpretation of an individual. |
| 5. The terms used to describe the model by the user should be generally positive. | Reactions: positive – most reactions concerned the overview that the model created. | Reactions: positive – especially with regards to the completeness and cohesion of the model | Reactions: positive – especially with regards to applying the model to specific improvement projects |

### 7.6.3 Test 3: Usefulness of the AMDI Model

This section describes the results of the tests on usefulness and answers research question 5. Research question 5 asks: How does the AMDI model improve understanding of asset management through IoT? Answering this question through the use of test case studies involves a discussion of the usefulness of the AMDI model as described in section 7.1. Included in the discussion of the usefulness of the model is a discussion of the proofs of the design propositions.

Criteria 1 of the usefulness test (Table 7-1), testing the null hypothesis (Yin, 2009), tests if the AMDI does not improve understanding of asset management through IoT organizations as IoT adoption occurs by chance only. Improving understanding of asset management through IoT adoption was observed in 3 different exploratory case studies and 3 test case studies and has been discussed at length in literature. The case

studies were studied independently of each other and in all the cases we were able to observe that IoT adoption had significant impact on traditional asset management processes and occurred due to a result of specific needs and interventions (see Chapter 4). This is also in line with other studies which describe adoption of innovative technologies (Aarons et al., 2011; Feldstein & Glasgow, 2008). We therefore argue that we may reject the null hypothesis.

*Tests on Design Proposition 1*

Criteria 2 (Table 7-1) provides the criteria for testing the first part of design proposition 1 and states that the AMDI model should provide actionable insights into the influence of people asset management through IoT. Adoption theoretical frameworks identify key people characteristics that are positively associated with adoption of new technologies, including skills and experience, knowledge of applying an innovation, and general fit with adopter characteristics such as learning style and tolerance of ambiguity (Solomons & Spross, 2011). Application of the AMDI model shows that agents have a particularly large influence on asset management through IoT, and adoption readiness is of paramount importance for successful adoption. For example, interviewees at Stedin mention great importance being placed on the learning agility of Stedin employees, and RWS has a mature reward system whereby employees are financially rewarded for ideas with an innovation component. This is in line with Greenhalgh et al. (2004) and Solomons & Spross (2011), who suggest that assessment of attitudes toward change, endorsing a holistic approach towards quality improvement, and utilizing a reward system are positively associated with adoption of new technologies. However, application of the AMDI model also shows that people in asset management business processes need to learn new skills to be able to understand and interpret IoT data. Interviewees reported that asset managers are required to be "much more data aware than before, and the line between the data scientist and the asset manager is becoming much thinner". For example, both Stedin and RWS have developed a "Data-Lab" alongside already available risk analysis teams in which dedicated data scientists work with asset managers in an holistic quality improvement process as suggested by Solomons & Spross (2011). Both Stedin and RWS identify a lack of data science skills as major stumbling blocks in asset management through IoT and the Data Governance Officers at both organizations have initiated training programs designed to improve data awareness and analytics skills within the organization. Results of the test cases suggest that a successful

method (employed by both Stedin and RWS) to improve skills and awareness of IoT is that of development of communities of practice. This is in line with the suggestions of Greenhalgh et al. (2004), who suggest that social ties within and outside an organization, extensiveness, and quality of such networks are positively associated with adoption of new technologies.

Criteria 3 (Table 7-1) provides the criteria for testing the second part of design proposition 1 and states that the model should provide actionable insights into the influence of technical innovation characteristics on asset management through IoT. Adoption theoretical frameworks have characterized adoptable innovations as being clear in purpose and simple to use, observable, and transferrable (Oldenburg & Glanz, 2008). Data governance should ensure that data is aligned with the needs of the business, including ensuring that data meets the necessary quality requirements. For example, the level of accuracy and timeliness of the data being generated by the WIM is essential for traffic warden to be able to react in a timely fashion and with confidence in the results. Also, asset managers at Stedin need to have full confidence in the results of the smart meters in order to be able to properly balance the electricity loads of the mid-tension grid. The results of the test case studies show that IoT technology should be clear in purpose and simple to use to for asset management through IoT, and the test cases demonstrate that the model of AMDIs improves understanding of the component parts, in line with Oldenburg & Glanz (2008) who suggest that innovations should be observable and transferable.

According to Feldstein & Glasgow (2008), innovations that are coupled with existing processes are more likely to be adopted. The test cases show that adoption of IoT allows for more detailed and accurate predictive analysis changes for asset management purposes. For example, in energy grid management, greater availability of real-time data has increased trust in the asset management process and allows for greater predictability in risk-based decision-making. This has allowed decision-making to become partially automated due to the greater certainty as to when and which action needs to be taken. Ensuring alignment can take the form of defining, monitoring and enforcing data policies (internal and external) throughout the organization. The test cases show that ensuring compliance to privacy laws as well as maintaining increasingly sophisticated levels of security in IoT adoptions is becoming essential to successful asset management.

*Tests on Design Proposition 2*

Criteria 4 (Table 7-1) provides the criteria for testing design proposition 2 and states that the AMDI model should provide actionable insights into the influence of data governance on asset management through IoT. According to Aarons et al. (2011), an organization's absorptive capacity, the capacity to utilize innovative and existing knowledge may have a positive influence on adoption of new technologies such as IoT. With regards to the test cases, both RWS and Stedin have well-structured processes to incorporate new technologies and have developed strong relationships with knowledge institutes. For example, WIM was developed by RWS in cooperation with technical universities and private knowledge institutions. High levels of networks between cooperating organizations as enabling factor for the use of IoT in asset management is in line with Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou (2004) who show that multiple, informal inter-organizational networks, and general interconnectedness among organizations is positively associated with adoption of new technologies.

According to Wisdom et al. (2014), organizational norms, values, and cultures are critical to adoption of new technologies in organizations. This includes shared professional values (Mendel et al., 2008), and a culture of problem-solving (Oldenburg & Glanz, 2008). Application of the AMDI model shows that both RWS and Stedin can be characterized as having highly professional cultures with a reputation for "getting things done" and pride in maintaining high levels of professionalism and problem-solving in the face of complex challenges, in line with Oldenburg & Glanz (2008). But the test cases also show that this culture of shared professional values originates from a network of professionals as opposed to a hierarchical structure. At both RWS and Stedin the presence of communities of practice was seen as positive influences in the dissemination of knowledge regarding asset management through IoT. This is in line with Frambach & Schillewaert (2002), who suggest that social persuasion and communication from peers within an organization help identify with and achieve adoption of new technologies in organizations.

However, the AMDI model also shows that management support positively influences asset management through IoT in the form of "championship" and leadership promotion as suggested by Aarons et al. (2011) and Feldstein & Glasgow (2008). This is depicted in the data governance class in which data governance roles take strategic (data owner), tactical (data steward) and operational (data manager) forms. For example, the executive management at the Department of Central

Information Management at RWS, as data owners, played an important role in championing the use of WIM data for asset management, as did the Director of Strategy and the Chief Data Officer at Stedin with regards to Smart Meter data. However, a number of interviewees in the test cases reported that the distance between senior management and operations meant that senior management had eventually little influence on the operational use of IoT in the asset management process, in line with the suggestions of Backer, Liberman, & Kuehnel (1986) that top-down leadership is negatively associated with adoption of new technologies in organizations. The suggestion being that tactical and operational professionals at RWS and Stedin prefer to "do things their own way". So whilst data owners champion the use of IoT for asset management, it is the data stewards and data managers who eventually take the operational decisions to implement IoT technology and trust the data. As such, results of the test cases suggest that it is inefficient to try to exert a hierarchical control over AMDIs and that typical characteristics of CAS should be taken into account when adopting IoT in asset management. This is in line with Greenhalgh et al. (2004) who suggest that a formalized, centralized organizational structure and heavy organizational coordination requirements are negatively associated with adoption of new technologies. For example, interviewees at Stedin sited "long waiting periods and competition with backlog from regular IT service provision" as stumbling blocks to asset management through IoT. At Stedin, decisions regarding prioritization of resources are made once every 3 months in a "Big-Room Planning", in which innovations compete for resources with regular service provision requirements. If a particular innovation is not accepted in a particular big room planning, another 3 months are required before a new prioritization can be made.

However, a compromise should be made, as sound data governance is required to ensure that IoT can provide trusted data for decision making (Dawes, 2010). Application of the AMDI model shows that decision processes have been changed to deal with the real-time nature of the data, and reveals that asset managers have had to adapt and develop new skills and capabilities to adapt to changing roles and changing processes. However, as suggested by Greenhalgh et al. (2004), with regards to asset management through IoT, the organization of data governance should not be seen as a "one size fits all" approach (Wende & Otto, 2007). For example, with regards to Smart Meters and Hoog Dalem, prosumers retain ownership of the data whilst Stedin maintains a stewardship role, whereas with WIM, RWS has an ownership role and performs much of the data management itself.

*Tests on Design Proposition 3*

Criteria 5 (Table 7-1) provides the criteria for testing design proposition 3 and states that the model should provide actionable insights into the influence of socio-political environments asset management through IoT. Adoption theoretical frameworks have identified socio-political and external factors that can influence adoption of new technologies (Damanpour & Schneider, 2006). Environmental characteristics may refer to the sector within which the organization operates, or may represent cultural, societal, political or geographical conditions (Wejnert, 2002). In our AMDI model, we include three relevant environmental factors of cultural, physical and political environments within the asset management sector. The three test cases occur at differing levels which allowed us to test the influence of urbanization and community size on asset management through IoT. According to Damanpour & Schneider (2006), urbanization and development around an adopting organization have a positive association, as organizations in urban areas tend to have easier access to service providers and face more diverse and complex environments than those in rural areas (Boyne, Gould-Williams, Law, & Walker, 2005). However, the test case on the local level, Hoog Dalem, occurs in an area of relatively low level of urbanization, and the regional and national level test cases occur throughout areas of varying levels of urbanization. And yet the level of IoT adoption in each of the test cases is high. What application of the model does reveal throughout all the test cases is that all the cases have a high level of environmental complexity and are relatively wealthy, having access to high levels of financial and other resources. According to Daft, Murphy, & Willmott (2010), greater environmental complexity leads to more numerous, specialized and interconnected organizational parts, stimulating higher rates of innovation and change, and Damanpour & Schneider (2006) show that resources also provide local governments of wealthier communities with a greater ability to prepare organizational and community members for implementing the new programs or services. As such, the results of the test cases show that organizational wealth and complexity may have a larger influence on asset management through IoT than other factors such as urbanization. This is in line with Mendel, Meredith, Schoenbaum, Sherbourne, & Wells (2008) who identify financial incentives and reward systems as being necessary for successful adoption of new technologies.

According to Aarons et al. (2011), external policy and regulation are positively associated with adoption of new technologies, including specific enactment of policies, legislation, or regulations on innovation adoption. This is demonstrated in the AMDI model as, for example, the

adoption of smart meters in the electrical grid has been driven largely by European Union directives. Furthermore, European Union and Dutch law also drive data privacy protection regarding the smart meters. However, the results of applying the AMDI model to the test cases show that unclear or incomplete political and legal frameworks can also hinder asset management through IoT, as a number of interviewees responded that "much more could be done with the data provided by the smart meters", but uncertainties surrounding the use of smart meter data restricted the potential benefits. In the Netherlands a number of households have refused the smart meter due to privacy concerns. This shows that the political and cultural climate also needs to be a fit if asset management through IoT is to be enabled as suggested by Glasgow (2003). Similarly, a lack of defining legal frameworks surrounding the use of WIM for complete automation of law enforcement means that physical checks still need to be made. Based on Glasgow (2003) and the results from our test cases, we developed the following model, depicted in Figure 7-30 below. Application of the AMDI model shows that political directives can be a strong driving force for asset management through IoT, if the legal framework is clear and enforceable.

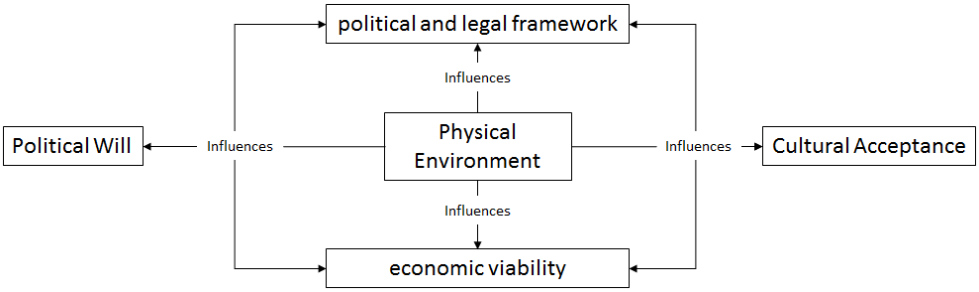


Figure 7-30: The influence of political, cultural and physical environments on asset management through IoT

According to Damanpour & Schneider (2006), most studies on innovation adoption tend to focus on a single dimension such as organizational factors, as organizational factors tend to be deemed to be primary determinants of innovation adoption in organizations (Subramanian & Nilakanta, 1996). However, application of the model in the test cases shows that asset management through IoT is multi-dimensional, being influenced by factors within several dimensions including: environmental; organizational readiness; technical adoption characteristics; and people. As such the model provides insight into the salient factors of each dimension and their relative explanatory power on

asset management through IoT. In this way, the AMDI model enables IoT adoption in asset management organizations, improving asset management. Table 7-7 below summarizes the answer to research question 5: Does the AMDI model enable IoT adoption in asset management organizations, improving asset management?

Table 7-7: A summary the evaluation of the AMDI model as enabling IoT adoption in asset management organizations and answer to research question 5

| Design Proposition | Evaluation Criteria | Result of the Test Cases | | |
|---|---|---|---|---|
| | | RWS: WIM | Stedin: Smart Meters | Stedin Hoog Dalem |
| DP 1. | 2. The model should provide actionable insights into the influence of people on asset management through IoT.<br><br>***Suggested Actions:***<br>- *Carry out data awareness programs*<br>- *Develop data science capabilities in the organization*<br>- *Develop data privacy awareness* | Agents have a particularly large influence on asset management through IoT at RWS, and adoption readiness is of paramount importance for successful adoption of IoT in AM. To mitigate this, Data Governance Officers have initiated training programs designed to improve data awareness and analytics skills within the organization. | People in asset management business processes need to learn new skills to be able to understand and interpret IoT data. Stedin has identified a lack of data science skills as a major stumbling blocks in the adoption of IoT in asset management. | Users of the infrastructure also need to become more aware of how their data is used and how their data could be used for their benefit and also in violation of their privacy. |

| Design Proposition | Evaluation Criteria | Result of the Test Cases | | |
|---|---|---|---|---|
| | | RWS: WIM | Stedin: Smart Meters | Stedin Hoog Dalem |
| DP 1.<br><br>***Suggested Actions:***<br>- *Ensure standardization of IT systems and protocols*<br>- *Implement regular auditing to monitor privacy and security compliance* | 3. The model should provide actionable insights into the influence of technical innovation characteristics on asset management through IoT. | IoT technology provides more detailed and accurate predictive analysis, increasing trust in the asset management process and allowing for greater predictability in risk-based decision-making. | AM through IoT requires significant (non-trivial) changes to current operational systems due to the multitude of standards used in the industry. | Ensuring compliance to privacy laws as well as maintaining increasingly sophisticated levels of security in IoT is becoming essential to successful asset management. |
| DP 2.<br><br>***Suggested Actions:***<br>- *Develop contracts between actors*<br>- *Cultivate a culture of data sharing*<br>- *Formalize ownership and responsibilities for data* | 4. The model should provide actionable insights into the influence of data governance on asset management through IoT. | Informal data governance is achieved through contract forming. At RWS, a culture of shared professional values originates from a network of professionals as opposed to a hierarchical structure. | Stedin is in the process of adopting a formal data governance structure in which the DG Officers need to play a coordinating role. The model gives insight as to the data ownership domains, and provides a framework for defining data quality requirements. | Application of the model shows that data governance is not straightforward as the data owner is a client of Stedin and not Stedin. Application of the model shows that Data Stewards at Stedin should be aware of their responsibilities towards the privacy of the data owners. |

| Design Proposition | Evaluation Criteria | Result of the Test Cases | | |
|---|---|---|---|---|
| | | RWS: WIM | Stedin: Smart Meters | Stedin Hoog Dalem |
| DP 3.<br><br>***Suggested Actions:***<br>- *Develop understandable strategies and clear business cases based on fact and regard for the political will.* | 5. The model should provide actionable insights into the influence of socio-political environments on asset management through IoT. | Application of the model shows that organizational wealth and complexity of environments may have a larger influence on AM through IoT at RWS than other factors such as urbanization. This is an important insight for RWS as RWS manages highways which largely occur outside of urban areas. | Application of the model shows that external policy and regulation, including specific enactment of policies, legislation, or regulations have a large impact on AM through IoT at Stedin. | Application of the model shows that unclear or incomplete political and legal frameworks can hinder IoT adoption in asset management, and that the political and cultural climate needs to be a fit. |

## 7.7 Conclusions

Case study research was used as the methodological approach to evaluate the validity and generalizability of the AMDI model within the contemporary phenomenon of asset management through IoT. The test case studies are of a descriptive nature and aim at describing the case in terms of the AMDI model. The objective of this chapter is to answer the final research question, RQ 5: *how does the AMDI model improve understanding of asset management through IoT*? The chapter evaluated the AMDI model by using the model to describe in detail three IoT cases in the asset management environment. The first case described was that of highway management to enforce overloading laws, known as Weigh-in-Motion. The case described was at the national level spread over a wide geographical area, and although the number of measuring stations was relatively small, the variety of sensors was large. The second case was that of the adoption of smart meters to manage a regional energy grid (electricity and gas). The third case was similar but looked at the use of

IoT to assist the provision of flexible energy sources to a local community, Hoog Dalem.

*Test1: Validity*
We may conclude that the cases were comparable in that they were all IoT adopters in the asset management domain, but the differences in the cases also demonstrated that the model was valid for asset management organizations and generalizable across organizational levels.

*Test 2: Usability*
We may conclude that the AMDI model is usable conform the defined criteria. The model has a broad scope, which means that very few people are able to work with the model in its entirety alone. However, this may also be regarded as one of the strengths of the model in that it brings people from different subject areas together to discuss and view the infrastructure from different perspectives. However, we acknowledge that achieving the situation whereby all required individuals were in one room at the same time was challenging.

*Test 3: Usefulness*
*Design Proposition 1: Components* – Results of the test cases also reveals that asset management through IoT is multi-dimensional, being influenced by factors within several dimensions including: organizational readiness; technical adoption characteristics; and people. Application of the AMDI model shows that agents have a particularly large influence on asset management through IoT, and adoption readiness is of paramount importance. The results of the test case studies also show that IoT technology should be clear in purpose and simple to use to enable asset management through IoT. We therefore conclude that the model improves understanding of the component parts of AMDIs.

*Design Proposition 2: Data Governance*
Results of the test cases show that ensuring alignment can take the form of defining, monitoring and enforcing data policies (internal and external) throughout the organization. The test cases show that ensuring compliance to privacy laws as well as maintaining increasingly sophisticated levels of security in IoT is becoming essential to successful asset management. Furthermore, sound data governance is required to ensure that IoT can provide trusted data for decision making. Application of the AMDI model shows that decision processes have been changed to

deal with the real-time nature of the data, and managers need to adapt and develop new skills and capabilities to be able to interpret the data.

*Design Proposition 3: Environments*
Application of the model shows that organizational wealth and complexity of environments may have a larger influence on asset management through IoT at RWS than other factors such as urbanization, and that political directives can be a strong driving force for asset management through IoT, if the legal framework is clear and enforceable.

# Chapter 8 Discussion and Conclusions

*"Why then, lead on. O that a man might know*
*The end of this day's business ere it come!*
*But it sufficeth that the day will end,*
*And then the end is known. Come, ho! Away!"*
**- William Shakespeare (Julius Caesar: Act-V, Scene-III)**

## 8.1 Introduction

In this research, our objective was to develop a model of AMDIs that improves understanding of asset management through IoT. We anticipated that IoT adoption introduces unexpected changes within asset management and so we applied Duality of Technology theory (Orlikowski, 1992), confirming the dual nature of IoT in asset management. Second, we identified the complexity of AMDIs and confirmed the necessity of viewing AMDIs as CAS when introducing new technologies such as IoT. On the basis of the insights provided by confirming the duality of IoT in asset management and by confirming the necessity of viewing AMDIs as CAS, we developed a model of AMDIs which improves understanding of asset management through IoT. For example, by explicitly outlining the relationship between asset managers as users of IoT and the need for building trust in the system through transparency and knowledge development, application of the model confirms the belief that, within the context of our case studies, asset management organizations with a hierarchical organizational structure are less equipped to adopt IoT and that a more network-based, organic organizational structure may provide a better fit for asset management through IoT as suggested by Damanpour & Gopalakrishnan (1998).

Maintaining public utility infrastructure is a complex process, especially when organizations which are tasked with this face increasing workloads and ever decreasing budgets. In order to maintain and improve services in the face of these constraints, organizations often turn to asset management as a way of increasing efficiency and effectiveness.

However, effective asset management decision-making requires large amounts of quality data, and traditional methods of data collection are proving inadequate to meet the current and future information needs of asset managers. Instead, more and more, asset management organizations are looking to innovations such as IoT to provide the data required to drive decision-making. Seamless adoption of IoT in asset management is not straightforward, and asset managers are not always inclined to trust the data and the information which IoT may provide. Furthermore, as a dual technology, the introduction of IoT often introduces changes to asset management which are often not entirely anticipated. Assuming that the answer to meeting the data needs of asset managers may lie with IoT due to the vast amounts of data which IoT produces, we therefore wished to improve understanding of asset management through IoT. As such, the main objective of the research was to develop a model of AMDIs that improves understanding of asset management through IoT.

We developed a framework of research questions which guided us in achieving our objective. First we looked at how IoT improves asset management and how IoT adoption may affect asset management in expected and unexpected ways. We wanted to know how IoT would be used in asset management, and what the benefits of asset management through IoT are, but also, what potential risks asset management through IoT poses. We investigated these questions by first reviewing state of the art literature. Our literature review revealed that little systematic research had been done on how IoT affects asset management or how IoT data should be governed. In the literature review we were able to list potential uses, benefits and unexpected risks to the organization which IoT carries. The literature review showed that the most important uses of IoT in asset management are coupled with the data that IoT produces. Accessing this data allows the asset management organization to use it for multiple purposes, often unrelated to the original operational purpose. For example, Hentschel et al. (2016) suggest that IoT can be used to trigger alarms when sudden increases in sound, light and temperature, which could indicate a fire or an explosion, occur. This same data could also be leveraged for increased efficiency in various public service applications such as inspection schedules, public facility management, urban infrastructure maintenance, intelligent transportation services, and emergency situation monitoring (Zhang et al., 2015).

However, the literature review also revealed that most of the uses, benefits and risks discussed in the literature were expected uses, benefits or risks with little factual evidence to back-up the claims. We therefore

utilized the case study method to investigate real world examples of asset management through IoT to gain systematic evidence of how IoT may affect asset management. Three exploratory case studies (LMW, Ground Water Levels, and BOS) were performed using the Duality of Technology theory and CAS theory as lens as suggested by (Yin, 2009). The exploratory case studies confirmed the belief that IoT can improve the data-driven capabilities of asset management organizations (Boos et al., 2013) thereby improving operating performance at varying levels throughout the organization (Zhang et al., 2015). For example, LMW allows RWS to predict rising water levels with much greater confidence, allowing operations such as the closing of important storm surge barriers to be automated. But due to the dual nature of IoT, the exploratory case studies also showed that asset management through IoT often carries unexpected risks, leading to unanticipated changes. For example, the diversity in terms of data communication methods and capabilities, computational and storage power, energy availability, adaptability, mobility, etc. (Zeng et al., 2011), can lead to operational risks such as difficulty in employing qualified personnel, lack of specialists, and personnel skill shortage to operate new applications (Speed & Shingleton, 2012; Yazici, 2014), as well as insufficient IoT oriented training and educational activities (Harris et al., 2015). This can mean that asset management organizations need to invest in new training facilities, and that people need to develop new skills, which in turn may lead to new insights and developments of the technology. For example, to meet this need, RWS has created a data lab, a new department staffed by people with specific data science skills.

Furthermore, the use of CAS theory as lens in our exploratory case studies revealed that asset management through IoT is multi-dimensional, being influenced by factors within several dimensions including: environmental; organizational readiness; technical adoption characteristics; and people. It became clear that, just like real world asset infrastructures, AMDIs are CAS. Introducing innovative technologies can therefore have wide ranging effects due to complex relationships between infrastructure components and the rules that agents have developed during their interactions. For example, coordinating data management at Water Authority Delfland has required the organization to identify ownership of the data so that roles and responsibilities can be correctly allocated.

As discussed above, our aim was to improve understanding of asset management through IoT, so once we understood how IoT may be used in asset management and what the effects of IoT adoption may be

on the organization and the people involved, we realized that understanding and communicating the structure and relationships of objects and agents operating within the AMDI would help reduce the risk of asset management organizations being confronted with unexpected structural changes whilst adopting IoT. We believed that using a design science approach to develop a model of AMDIs which accommodates IoT would improve the understanding of the impact of IoT on asset management, and help communicate predicted changes to the AMDI, thus improving understanding of asset management through IoT. We therefore designed a model of AMDIs based on the requirements gathered during the exploratory case studies, and based on design propositions which form the basis of our theory of improving understanding of asset management through IoT. In a nutshell, our design propositions propose that understanding and communicating the components, data governance and environments of the AMDI will bring actionable insights to light which have a positive impact on asset management through IoT.

Following the design science paradigm, we wished to know if our model of AMDIs did in fact improve understanding of asset management through IoT by enhancing our understanding of the impact of IoT on asset management and communicating the effects that IoT adoption may introduce. We decided to use the case study method as described by (Yin, 2009) to test the usability of our model, and to draw conclusions on the proofs of our design propositions. Three test case study were investigated using the model. Within the context of the test cases the model was tested for usability. The design propositions were tested on the basis of usefulness of the model, usefulness being a characteristic of usability. In other words, we wished to know if the model provided insights into how components, data governance and environments affect asset management through IoT. The results showed that the model complied with the defined criteria as to usability, and also provided insight into effects of components, data governance and environments on asset management through IoT, proving the propositions. For example, application of the model shows that the complexity of AMDIs and the dual nature of IoT means that, within the context of the case studies, it is inefficient to exert a hierarchical control over AMDIs when adopting IoT in asset management. As such, Stedin has begun adopting an agile, organic structure meaning that a more networked approach is being taken to development which has improved the IoT adoption process.

As asset management through IoT can be seen as a continuous process, conclusions can be drawn with regards to the adoption process as well as to the desired end state. Section 8.2 of this chapter summarizes

the conclusions presented in this research as answers for each of the research questions. Section 8.3 of this chapter reflects on the scientific and societal contributions of the research and discussions the implications of the conclusions. Section 8.4 discusses the short-comings and limitations of the research. Section 8.5 concludes the dissertation by discussing a potential research agenda for IoT AMDIs.

## 8.2 Conclusions

This section outlines the conclusions drawn in this research. The conclusions are grouped according to the research questions and describe conclusions relating to the process implementing asset management through IoT and conclusions relating to the desired end-state of asset management through IoT.

### 8.2.1 Conclusions Relating to Research Question 1

Because our objective was to develop a model of AMDIs that improves understanding of asset management through IoT, we were interested in how IoT improves asset management, and how asset management might change as a result of these improvements or as a result of the adoption of IoT. We therefore anticipated that IoT is a dual technology, but we needed to confirm the applicability of Duality of Technology theory (Orlikowski, 1992). Furthermore, as physical infrastructure is more and more regarded as being CAS, and the AMDI should reflect the physical infrastructure it represents, we also wished to confirm the applicability of CAS. Our first research question was therefore formulated as follows: *how can IoT improve asset management*? We answered this research question in chapters 3 and four by means of a literature review and by investigating three exploratory case studies in which we confirmed the duality of IoT adoption in asset management and confirmed the necessity of viewing AMDIs as CAS when adopting IoT in asset management. In the literature review and the exploratory case studies we discussed a number of innovation adoption issues related to uses, benefits and risks of asset management through IoT. Answering this question also had an intrinsic benefit, as according to Solomons & Spross (2011) continuous assessment of benefits and risks can have a positive effect on adoption of new technologies in organizations.

*Process related conclusions*:
The literature review and exploratory case studies show that, within the context of the case studies, benefits and unexpected risks to the asset

management organization due to IoT adoption can occur at both individual and institutional levels and within multiple dimensions of an organization, making it difficult to identify specific causal relationships for success or failure of asset management through IoT. For instance, when the strategic dimension is not emphasized, then important organizational issues are also often not addressed. This is reflected in the AMDI model in the relationship between the strategic dimension, the data policy and data governance alignment. Application of the model shows that a lack of data policies in asset management organizations may lead to misalignment of goals with mission and priorities. Application of the model in the test case studies showed that a data policy outlining the chosen architectural directions is important in creating trust in the efficacy of IoT as new technology to outperform traditional asset management practices. The test case studies show that it is insufficient to merely present asset managers with a list of uses and benefits and expect them to automatically adopt IoT within the asset management process. Instead, there needs to be a specific reason for central adoption of IoT in asset management, which, although sounds "obvious", is not always the case. It is not uncommon for organizations to introduce IoT with the idea that the application will be found once the technology is available. One of the main reasons for the success of WIM, for example, is that the system performs its primary duty of monitoring overloading of freight traffic extremely well. The IoT implementation needs to resolve a specific issue such as being able to automate specific processes based on real-time evidence. On the basis of the points raised above, we therefore note that the fit of IoT, as new technology, with organizational culture, knowledge, current practice, and task performance has a positive influence on asset management through IoT within the context of our case studies. As such, in line with Aarons et al. (2011) and Feldstein & Glasgow (2008), *we conclude that, in the context of the case studies, the goodness-of-fit between the solution provided by IoT and the needs of the asset management organization is critical for asset management through IoT*.

As discussed above, in the exploratory case studies we identified trust as being critical to acceptance of IoT in asset management. Psychological resistance to IoT can have a strong negative influence on the acceptance of IoT by asset managers. Asset managers therefore need to be able to trust the system in order to have the confidence to make correct decisions at the right time based on secure and correct data. However, the case studies also show that asset managers often have an inherent distrust of systems over which they have little understanding and control. The relationship between the alignment class of data governance

and the agent class in the model outlines the relationship between agents and trust in the data based on data quality and, as demonstrated in the test case studies, underlines the importance of improving data management and analysis skills and knowledge amongst asset managers. Similarly, the data governance organization class and its relationships in the model also underlines how IoT adoption risks in asset management are related to security, privacy and data sharing. Insights created by the model during the test case studies show the importance of data security and privacy by design, as seemingly innocent disclosure of user data could reveal sensitive information such as personal habits and unauthorized access to this information can severely impact user privacy. As such, data produced by IoT devices in asset management can be misused which contributes to a severe lack of trust in the IoT systems. We are therefore also able to concur with Backer et al. (1986) and *we conclude that, within the context of the case studies, fostering trust in the system by ensuring system and process security is critical for asset management through IoT.*

Interviewees in the exploratory case studies suggested that having executive management support was essential for success when implementing IoT, as staff felt it important to know that executive management saw the development as being a priority and supported the decision to move towards a more data-driven format. Management support is often stated as being a key success factor for improving processes (Feldstein & Glasgow, 2008). From a management perspective, improving trust in IoT often can be stimulated by adopting a "champion" role, as management support is often seen as being important when dealing with adoption of innovations. However, the exploratory case studies also show that the engagement of senior leaders in asset management organizations is often prioritized, so that implementation efforts with lower priority may not receive sufficient attention by lower management levels. Reflecting this, application of the model shows that, in the context of the case studies, strategic goals related to the adoption of IoT should be promoted across all organizational levels and clear communication of those goals are important for achieving expected benefits. For example, an important class in the model is the data governance *alignment* class which relates the solution provided by IoT to specific business requirements, in line with the findings of Feldstein & Glasgow (2008). The application of the model in the test cases showed that there is value to including representatives from all involved departments and that executive management roles are most effective when the executive manager assumes a championship role, promoting the asset management through IoT as a priority for the organization. *We*

*therefore conclude that, within the context of the case studies, management support in the form of "championship" and leadership promotion positively influences asset management through IoT*.

*End-state related conclusions:*
However, we have also noticed that, in the exploratory case studies, the distance between senior management and operations meant that senior management had eventually little influence on the acceptance of IoT by asset managers and we suggest that frameworks which focus on this aspect of management tend to overlook the negative effects of micro-management by senior management. In fact, the exploratory case studies revealed that, in the context of the case studies, exercising a hierarchical control over AMDIs can have a negative influence on achieving benefits and being able to mitigate risks due to unexpected changes whilst adopting IoT in asset management. As discussed above, as users, asset managers need to develop trust in the IoT system before accepting the results and recommendations provided by the system and allowing themselves to be data-driven. In line with the suggestions of Backer et al. (1986) the data governance *organization* class illustrates that top-down leadership can be negatively associated with asset management through IoT. Application of the model in the test cases showed that staff felt most empowered when working in a self-managing format with management setting priorities. *We therefore conclude that, within the context of the cases studies, it is inefficient to exert a hierarchical control over asset management through IoT*. This is also in line with Greenhalgh et al. (2004) who suggest that a formalized, centralized organizational structure and heavy organizational coordination requirements are negatively associated with adoption of new technologies.

### 8.2.2 Conclusions Relating to Research Question 2

The confirmation of the applicability of CAS to AMDIs provided us with a framework for modelling AMDIs. As such, we wished to investigate precisely what an AMDI consisted of and what the potential relationships were between classes of objects within the AMDI. Research question 2 of this research was therefore formulated as follows: *what are the elements and behaviors of AMDIs that enable asset management through IoT*? We answered this question in chapters 3 and 4 by means of a literature review and 3 exploratory cases studies in which we investigated a number of innovation adoption issues related to the socio-political, cultural and physical environmental characteristics of AMDIs, IoT system

characteristics and people characteristics influencing asset management through IoT.

*Process related conclusions:*
Environmental characteristics may refer to the sector within which the organization operates, or may represent cultural, societal, political or geographical conditions (Wejnert, 2002). The results of the case studies confirm this and show that asset management organizations with a high level of environmental complexity that also have access to high levels of financial and other resources are more enabled to adopt IoT. For example, although the cultural, political and physical environments in which LMW is managed presents unique challenges, RWS continues to manage it to an exceptional level of quality. RWS is reported to have access to sufficient financial resources, has a broad knowledge base and a strong political lobby. Damanpour & Schneider (2006) have shown that urbanization and development tend to have a positive effect on adoption of innovations in organizations. However, we do not see this trend in this research. As such we believe that urbanization itself may be a confounding variable, as many urbanized areas may have larger access to financial and other resources than most rural areas. However, the two are not necessarily mutually exclusive. For example, the cases studies did not necessarily occur in urbanized areas, in fact, LMW and Water Authority Delfland can arguably be classified as being largely rural. Instead, by including the environment class and by describing the relationship this class has with, for example, the agent class, our model makes the impact of environments on IoT adoption more specific. The application of the model in the test cases shows, for example, that Stedin is able to maintain a high standard of service in rural and urban areas alike, but focus is often placed on service to areas of greater social, economic or political importance. Therefore, we agree with Daft et al. (2010) and *conclude that, within the context of the case studies, greater environmental complexity in combination with access to sufficient financial resources may stimulate asset management through IoT.*

Many asset management settings resemble non-competitive, monopolistic environments, and our case studies were no different. According to Herder et al. (2011), this should result in less incentive for organizations to quickly absorb best practices than would be expected in a competitive setting. However, the exploratory case studies show that this trend may be offset by political pressure. For example, as suggested by Aarons et al. (2011) in the case studies we noticed that external policy and regulation may be positively associated with adoption of new

technologies, including specific enactment of policies, legislation, or regulations on innovation adoption. In the model this is reflected in the relationships between the environment class, the agent class and the data class. This is demonstrated in the test case studies by the adoption of smart meters in the electrical grid being driven largely by European Union Directives. Furthermore, the application of the model in the test case studies also shows that unclear or incomplete political and legal frameworks can also hinder IoT adoption in asset management. For instance the research shows that more could be done with the data provided by the smart meters, but uncertainties surrounding the use of smart meter data restricted the potential benefits. In the Netherlands a large number of households have refused the smart meter due to privacy concerns. As such, we agree with Glasgow (2003) and *conclude that the political and cultural climate needs to fit asset management through IoT*.

*End-state related conclusions:*
According to Herder et al. (2011), most public utility asset management organizations include a variety of actors and stakeholders which may be different to most commercial enterprises. This multi-agent setting complicates the implementation of innovation as decision-making may often involve a long process which could involve political trade-offs and stakeholder consultations (Herder et al., 2011). In the exploratory case studies it became clear that *people* related changes wrought about by IoT adoption in asset management may be seen in the way people themselves have to adapt to new technologies. For example, new capabilities, skill sets and new ways of thinking were required within RWS to be able to leverage the full benefits of LMW and adopt a data-drive decision-making process. It became clear in the exploratory case studies that asset managers need to become much more data aware than before, and the line between the data scientist and the asset manager is becoming much thinner. This is reflected in the model in the agent class and in the relationship between the agent class and the data class. Asset managers need to have a greater awareness of the possibilities and pitfalls of IoT to improve decision-making. Applying the model in the test case studies reveals that both Stedin and RWS have developed a "Data-Lab" alongside already available risk analysis teams in which dedicated data scientists work with asset managers in an holistic quality improvement process as suggested by Solomons & Spross (2011). *We therefore conclude that, within the context of the case studies, improving the level of knowledge and awareness of IoT of the asset managers has a positive effect on asset management through IoT*.

In line with Solomons & Spross (2011), the exploratory case studies reveal that when there is no attention to the cultural dimension of asset management through IoT, improvement results are not acknowledged by the organization, success is not rewarded and improvement behaviors do not become embedded in practice. This suggests that the ability of tactical staff to observe meaningful results and achieve expected benefits is important to implementing and sustaining asset management through IoT as suggested by Feldstein & Glasgow (2008). The case studies revealed that positive initial results provided by IoT which are shared among peers generally promote confidence and self-efficacy among asset managers and that an adoption program that provides early results is important. This is reflected in the model in the agent class and its relationship with the data governance organization class. Application of the model in the test cases shows that developing communities of practice has had a positive influence on the development of skills and awareness of IoT. We therefore agree with Greenhalgh et al. (2004) and *conclude that, within the context of the case studies, organized social networks within and outside an asset management organization positively influence asset management through IoT*.

The exploratory case studies also show that IoT technology should be clear in purpose and be simple to use to enable adoption in asset management organizations, in line with Oldenburg & Glanz (2008) who suggest that innovations should be observable and transferable. For example, in the LMW system, combining information from devices and other systems using expansive analysis, has allowed RWS to automate existing asset management processes. For example, it is possible to combine data from sensors in water monitoring stations with other data such as weather data to predict water levels to a sufficient precision that automation of major events such as the closing of a storm surge barrier is possible. This is reflected in the technology class of the model and its relationship with the data class. Application of the model in the test cases reveals more detailed and accurate predictive analysis changes in Dutch highway management, and has allowed decision-making to become partially automated due to the greater certainty as to when and which action needs to be taken. *We therefore conclude that, in the context of the case studies, aligning IoT innovations with existing asset management processes has a positive influence on asset management through IoT*.

### 8.2.3 Conclusions Relating to Research Question 3

The applicability of CAS as framework for modelling AMDIs meant that we were particularly interested in the schema of AMDIs as CAS. During the

exploratory case studies we were able to identify the schema of AMDIs as data governance which is reflected in the model in the data governance parent class. As we saw during the literature review, little research has been done on data governance in asset management organizations. We therefore needed to expand our knowledge base on data governance in asset management through IoT. Research question 3 of this research was therefore formulated as follows: *what are the elements of data governance in AMDIs that enable asset management through IoT*? We answered this question in chapters 3 and 4 by means of a literature review and exploratory case studies in which we investigated concepts of data governance which influence asset management through IoT.

*Process related conclusions:*
Damanpour & Gopalakrishnan (1998) believe that due to the stability of the environments in which they occur, many asset management organizations such as public utility organizations have, in the past, tended to have a hierarchical or mechanistic organizational form, meaning that asset management organizations will adopt innovations infrequently. This explains how the rate of IoT adoption in asset management often tends to be low. According to Damanpour & Gopalakrishnan (1998), because of the stable environments surrounding asset management organizations, organizational change usually entails modifications to business processes and IT systems, forcing innovations to be incremental and to be designed to reuse existing systems in different configurations rather than to create new ones. Herder et al. (2011) believe that asset management organizations within the public sector need to be predictable and transparent. This may create a hesitation to apply new methods as witnessed by the resistance of asset managers to trust data driven insights. However, the exploratory case studies show that new challenges such as climate change are placing pressures on asset management organizations to find new ways to adapt to these challenges. Risks are becoming too great to work "on gut feeling" and to react slowly. This is reflected in the model in the agent class and its relationships with the data governance organization class. Application of the model in the test cases reveals that other asset management organizations are having to change their organization forms due to similar challenges. According to Damanpour & Gopalakrishnan (1998), organizational forms that are most effective in adopting innovations include the organic and adhocracy organizational forms (Quinn & Hall, 1983). In line with this thinking, application of the model shows that the test case studies have begun to form inter-functional teams which are being empowered to develop and

implement innovations quickly. For example, Stedin has embraced the concept of Agile development, in which multi-functional "scrum teams" work towards constant improvement of their product. This demonstrates a more organic structure in which the organization is designed to be a more creative environment with an emphasis on trust. As such, *we conclude that, within the context of the case studies, adopting a more organic organizational structure in which an environment of trust is created for inter-functional teams has a positive effect on asset management through IoT.*

*End-state related conclusions:*
However, the case studies also show that a formalized data governance structure which is a fit with the specific organization, does need to be implemented in order to enable IoT adoption in asset management organizations. This is because automating decision-making often incurs business process related changes which can be found in aligning complex data structures. For example, automating decision-making of water pumps with the BOS system at Water Authority Delfland means that decision making can be performed at a more strategic, regional level as opposed to at the local, operational level. This is reflected in the data governance alignment class. As such, as seen in the data governance organization class, it is important to ensure that data provenance is well organized so that it is clear where responsibilities and accountabilities lie throughout the data lifecycle. This may create tension in the organization due to a principle agent problem as suggested by Herder et al. (2011) in which the one who pays is not always the one who decides and is often not the one who benefits from the investment. It is therefore important that data provenance is organized in such a way that inter-departmental teams are aware of the goals behind IoT adoption so that they understand why certain activities need to be performed that may not necessarily have a direct influence on their part of the process. For example, when business processes become automated, people assume new or different roles and people-made decisions are often elevated to more strategical levels. This also often means changes in the organization as people are asked to perform other tasks in changing social and cultural environments and often in changing organizational structures. This is reflected in the model in the agent class and the roles the various play within the data governance organization class. Application of the model in the test cases reveals, for example, that Stedin is required to carry the costs of installing and maintaining the smart meters, although the decision was taken at the political level. Furthermore, it is the end-user and the energy provider

that has the primary benefit of the smart meter implementation. As such, with regards to organizational related changes brought about by IoT adoption and in agreement with Weber et al. (2009) there is no "one-size-fits-all" approach to data governance. W*e therefore conclude that, within the context of the case studies, instituting strong data governance procedures which align inter-functional teams behind a common goal has a positive influence on asset management through IoT*.

### 8.2.4 Conclusions Relating to Research Question 4

Once we had developed the knowledge base to a sufficient level, we built a model of AMDIs which provides actionable insights into previously unforeseen changes within asset management and communicates these insights efficiently so that asset managers are able to take appropriate action. Research question 4 of this research was therefore formulated as follows: *what does a model of an AMDI that accommodates IoT look like*? We answered this question in chapters 5 and 6 by discussing the best approach to modelling AMDIs and using the results of research questions 1, 2 and 3 as input to build the model.

*Process related conclusions:*
The case studies show that AMDIs are complex socio-technical systems and their complexity shows in the physical networks, and in the actor networks, as well as the combination of the two. For example, understanding socio-technical complex systems such as the LMW system requires knowledge of both the technical and the social systems – taking only a technical perspective would result in missing important information such as the impact of people on the choice of technology, or the impact of the organization structure on how people respond to adoption of IoT. This is in accordance with Weijnen et al. (2008), who suggest that the socio-technical complexity of infrastructure systems calls for the combination of object-oriented and agent-oriented perspectives. As suggested by Herder et al. (2008b), modelling the AMDI from either purely an actor perspective or from a technical system approach would either provide too little opportunity for modelling the reflectivity of the actors or would not provide enough detail for a complete design of the technical system. This research therefore made use of the "cross-over" modelling technique (Weijnen et al., 2008) which forces the modeler to consider problems from the agent perspective, whilst providing insight into known and unknown variables such as the relationship between agents. We therefore developed an agent based model using object orientation. Our model breaks up the AMDI into reusable, logical parts but

does not pose a limitation to the extensibility of an element. Application of the model in the test case studies shows that a combined approach to IoT adoption is essential. For example, Stedin is moving towards an object-oriented approach to asset management, with the introduction of a Stedin Logical Data Model, however, managing the network as a whole for energy distribution purposes also requires a separation of object and functionality, as whilst individual asset objects can be replaced or combined, their functionality seldom varies. As such we therefore argue that the AMDI model presented in this research also takes into account the typical characteristics of complex system design as put forward by Herder et al. (2008b, p. 26), that "design in the context of a socio-technical system should acknowledge and respect both the physical and the social reality and their respective rationalities". *We therefore conclude that cross-over modelling improves our ability to model AMDIs as complex systems and to better understand asset management through IoT*.

*End-state related conclusions:*
The exploratory case studies impressed on us the importance of interoperability and openness when designing models of AMDIs. For example, LMW is a system which uses multiple technologies, all of which need to communicate efficiently for the system to work according to specification. In the model we therefore chose to use open standard technologies to model the AMDI as they are widely accepted. This helped ensure sustainability of the model and allowed us to utilize other accepted and popular linked open data ontologies. Another advantage of using open standard technologies were the numerous supporting development environments and tooling available. In order to ensure interoperability we selected the World Wide Consortium (W3C) standards and recommended Semantic Web technologies. The model is built using the Resource Description Framework (RDF) as specified by the World Wide Web Consortium (W3C). RDF was originally designed as a metadata model and has come to be used as a general method for conceptual description or modeling of data. During the design phase of the research, 44 requirements of AMDIs were identified which improve understanding of asset management through IoT. The requirements were clustered according to use, system functionality and system behavior. Requirements according to use were classified as stakeholder requirements. Three main clusters of stakeholder requirements were identified. These include, improving performance analysis of infrastructure services using IoT, improving expectation management of infrastructure services using IoT, and improving infrastructure service

processes using IoT. Three main clusters of system component requirements were identified, namely, component implementation, data governance implementation and managing environmental effects. Four main behavioral requirements were identified, namely, dynamism, connectivity, emergence and adaptation. The requirements provided us with the practical requirements for enabling IoT adoption in asset management. Analysis of the case studies also provided us with two main propositions which helped us develop the theoretical implications of this research. Building on the foundation provided by the requirements and the theory proposed by the propositions, design principles were further defined at a more detailed level to provide scope and direction for the design. 70 component design principles were derived from the design propositions. 40 data governance design principles were used to support the governance driving the AMDI.

By modelling the AMDI, we were able to illustrate and simulate the basic components of AMDIs and their interrelationships. Application of the model in the test case studies showed that the AMDI model is successful in depicting the composition of concepts relating to IoT systems within asset management organizations. Essentially, application of the model in the test cases reveals that the model is a set of statements expressing relationships among the functional elements which include the technology, data, agents and environments. *We conclude that these constructs help us understand what the AMDI model looks like. We also conclude that these constructs help us to improve understanding of asset management through IoT by facilitating early detection and correction of system development errors, and improving understanding of the social impact of asset management through IoT*.

### 8.2.5 Conclusions Relating to Research Question 5

Once we had designed and built the model, we needed to test if the model was usable and useful. The test for usefulness essentially tests the design propositions outlined in Chapter 5. Research question 5 of this research was therefore formulated as follows: *how does the AMDI model improve understanding of asset management through IoT*? We answered this question in chapter 7 by analyzing the results of three test case studies. During the test case studies we performed three tests. The first test validates the test cases against the criteria for case study selection. The second test tests the usability of the model against the criteria for usability as outlined in chapter 2. As mentioned above, the third test tests the design propositions and thus the usefulness of the model for improving understanding of asset management through IoT.

As discussed in chapter 5, Sokolowski & Banks (2010) suggest that the added value of models lie with the communication and conveyance of the fundamental principles and basic functionality of the system which it represents. As such, following Sokolowski & Banks (2010), our model strives to:

- enhance our understanding of socio-political and technical IoT system requirements in an asset management environment,
- facilitate communication of IoT system details between stakeholders in an asset management environment and provide a means for collaboration between agents in the asset management organization,
- provide a point of reference for designers to extract system specifications for IoT adoption in asset management use cases, and,
- provide a method to document the IoT system for future reference.

Concluding whether or not the AMDI improves understanding of asset management through IoT therefore involves a discussion on the success of the model with regards to its compliance with the criteria defined in section 2.5.4, with respect to the added value that a model creates as suggested by Sokolowski & Banks (2010).

*Process related conclusions:*

As discussed above, with regards to the usability of the model, we initially wished to determine if the model is either incomplete or overly complicated. The test cases demonstrate that individuals for each of the object classes could be found. Furthermore, the robustness of the research with regards to the case study protocol (see Appendix D), as well as in-depth discussions with subject matter experts in the test cases and colleague researchers leads us to believe that extraneous object classes at the secondary level of the model are not present. However, case studies as a research method are inherently limited due to the fact that the researcher often has to infer logic based on incomplete data. Future research should take these limitations into account.

The model is built using the Resource Description Framework (RDF) as specified by the World Wide Web Consortium (W3C). RDF was originally designed as a metadata model and has come to be used as a general method for conceptual description or modeling of data (Hayes & Gutierrez, 2004). RDF is a way of recording information about resources (Powers, 2003). As such, the RDF schema (RDFS) used in the AMDI model imposes very loose constraints on its vocabularies whereas the ontology developed within the model adds additional constraints that increase the

accuracy of implementations of IoT in asset management organizations, allowing additional information to be inferred about the IoT system. For example, IT systems need to be able to transport, store and analyze large amounts of dynamic data at real time. As such, we argue that the model is compliant with the usability criteria and *we conclude that the AMDI model provides a point of reference for designers to extract system specifications for asset management through IoT, providing a method to document the IoT system for future reference.*

The test cases show that asset management organizations are currently experimenting with new data sources and that there is a general expectation that IoT will provide significant added value to asset management decision making. We identified three main changes to asset management decision-making processes due to IoT adoption which are: changing performance measurement of infrastructure services; changing perception management of infrastructure services; and changing improvement processes of infrastructure services. Application of the AMDI model shows that IoT adoption provides more detailed and accurate predictive analysis for asset management which provides greater predictability in risk-based decision-making. Earlier research (e.g. Solomons & Spross, 2011) has shown that regular analysis of the benefits and risks to innovation adoption has a positive influence on adoption of innovations in organizations. *We therefore conclude that the AMDI model enhances our understanding of socio-political and technical IoT system requirements in an asset management environment by providing insight into the uses, benefits and risks of IoT for asset management.* We thus argue that we may disregard the null hypothesis and *we conclude that asset management through IoT can be modelled as IoT adoption does not randomly occur, but rather occurs as a result of specific needs and interventions within asset management.*

The results of the exploratory case studies and literature review identified a number of socio-political and external factors that can influence adoption of new technologies (Damanpour & Schneider, 2006). Our AMDI model includes the cultural, physical and political environments within the asset management sector. With regards to the physical environment, Damanpour & Schneider (2006), believe that urbanization and development around an adopting organization have a positive association on innovation adoption. However, application of the AMDI model shows that having access to high levels of financial and other resources rather than urbanization is of particular influence. The suggestion being that urbanization is a confounding variable, as although there is often a correlation between urbanization and greater levels of

financial resources, this is not always a causal relationship. *We therefore conclude that our model enhances our understanding of socio-political IoT system requirements in an asset management environment by highlighting the need for access to high levels of financial and other resources.* This is in line with (Mendel et al., 2008) who identify financial incentives and reward systems as being necessary for successful adoption of new technologies.

Application of the AMDI model shows that clear and unambiguous policy and regulations have a strong positive relationship with asset management through IoT, but that the cultural environment can impact this relationship if the policy is unclear or if the political and legal frameworks are incomplete. For example, government policy regarding the adoption of the smart meter in the Netherlands was directly influenced by cultural concerns regarding privacy of the individual. In the Netherlands a number of households have refused implementation of the smart meter in their homes. This shows that the political environment can influence the adoption of innovations in organizations. For example, Aarons et al. (2011) show that external policy and regulation are positively associated with adoption of new technologies, including specific enactment of policies, legislation, or regulations on innovation adoption. *We therefore conclude that our model enhances our understanding of socio-political IoT system requirements in an asset management environment by communicating the need for a fit between the political and cultural climate and asset management through IoT.*

*End-state related conclusions:*

The AMDI model improves understanding of asset management through IoT by providing insight into the network of actors involved. We have already concluded that a culture of shared professional values originates from a network of professionals as opposed to a hierarchical structure. Furthermore, application of the model shows that the presence of communities of practice enables IoT adoption in asset management through the dissemination of knowledge regarding IoT. This is in line with Frambach & Schillewaert (2002) who suggest that social persuasion and communication from peers within an organization help identify with and achieve adoption of new technologies in organizations. The AMDI model does not disregard the influence of "championship" and leadership promotion as suggested by Aarons et al. (2011) and Feldstein & Glasgow (2008), but underlines the need for an organic organizational form to enable asset management through IoT as previously concluded. *We therefore conclude that the AMDI model facilitates communication of IoT*

*system details between stakeholders in an asset management environment and provides a means for collaboration between agents in the asset management organization. Furthermore, we also conclude that our model enhances our understanding of socio-political IoT system requirements in an asset management environment by providing insight into the relationships between actors in the asset management organization and how these relationships influence asset management through IoT.*

This research has shown that IoT adoption allows asset management decision-making to become partially automated due to the greater certainty as to when and which action needs to be taken. As such, IoT business processes need profound changes to include the IoT characteristics in the business processes. For example, asset management decision-making processes need to be changed to deal with the real-time nature of the data. As such, we have seen that business processes for asset management decision-making need to be reconfigured to include data governance so decision-makers can interpret the limitations and potential of the data and ensure that security and privacy is accounted for. Application of the AMDI model shows that ensuring appropriate management of the data to ensure compliance to laws and regulations is essential to asset management through IoT. Data governance is required to ensure that IoT can provide trusted data for decision making. However, data governance is not a "one size fits all" approach and the AMDI model provides functionality to model data governance so that it fits with a specific asset management organization. *We therefore conclude that our model enhances our understanding of socio-political IoT system requirements in an asset management environment by providing insight into the business process changes required to formalize data governance. Furthermore, we also conclude that the model provides means to facilitate communication of the necessary changes to the processes required to ensure compliance to privacy and security policy and regulations and to align the data products of the IoT system with asset management business process requirements.*

Top-down leadership is negatively associated with adoption of new technologies in organizations (Backer et al., 1986). As such, application of the AMDI model demonstrates that it is inefficient to exert a hierarchical control over AMDIs and that typical characteristics of CAS should be taken into account when adopting IoT in asset management. Instead, results of the test cases show that a more organic organizational structure should be utilized for asset management through IoT. The level of complexity regarding the inter- and intra-departmental relationships is such that

organizational silos can form an serious risk to successful asset management through IoT. *We therefore conclude that our model enhances our understanding of socio-political IoT system requirements in an asset management environment by providing insight into the required organizational structures of asset management through IoT. Furthermore, we also conclude that the model provides means to facilitate communication of the importance of these relationships between agents within the asset management organization.*

Adoption of IoT requires an IT infrastructure that can facilitate the new data sources and requires a good understanding of the data collected and its quality aspects. IoT technology should be clear in purpose and simple to use. The AMDI model improves understanding of the technical component parts of IoT systems in line with Oldenburg & Glanz (2008) who suggest that innovations should be observable and transferable. Furthermore, previous research has shown that innovations which are coupled with existing processes are more likely to be adopted (Feldstein & Glasgow, 2008). Application of the AMDI model shows that adoption of IoT allows for more detailed and accurate predictive analysis of the physical infrastructure, increasing trust in the asset management process and allowing for greater predictability in risk-based decision-making. *We therefore conclude that the asset management model enhances our understanding of the technical IoT system requirements in an asset management environment by providing an overview of the required technical components of IoT systems and how they fit together. Furthermore, we conclude that the model provides a point of reference for designers to extract system specifications for IoT adoption in asset management organizations, and provides a method to document the IoT system for future reference.*

Our final discussion looks at how the AMDI model improves understanding of asset management through IoT by providing insight into people related changes relating to IoT adoption. Application of the model shows that people in asset management positions need to learn new skills to be able to understand and interpret the data. The culture needs to be changed to move from physically based inspections to data driven inspection of assets. This is in line with Greenhalgh et al. (2004) and Solomons & Spross (2011) who suggest that assessment of attitudes toward change, endorsing a holistic approach towards quality improvement, and utilizing a reward system are positively associated with adoption of new technologies. Adoption readiness is of paramount importance for successful asset management through IoT and results of the case studies show that a lack of data science skills is major risk to

asset management through IoT. *We therefore conclude that the AMDI model enhances our understanding of people requirements for asset management through IoT.*

In this section we have discussed how our AMDI model enhances our understanding of the socio-political and technical system requirements of asset management through IoT with regards to environmental changes, technical changes, organizational changes and people changes. Furthermore we have discussed how the model also facilitates communication of these changes and the component relationships between the various stakeholders. We have shown how the model can be used to provide a point of reference for designers to extract socio-political and technical system specifications for asset management through IoT, and how the model provides a method to document the IoT system for future reference. *We therefore conclude that the AMDI model improves understanding of asset management through IoT.*

## 8.3 Reflections on the Research

Having discussed our research conclusions in the previous sections, we now take some distance from the collected data and findings and ask the question what this research implies and how it contributes to science and society. We also reflect on the strengths and limitations of the philosophies, methods and approaches used in the research and how these methods may have affected the results and our reasoning behind the conclusions. Finally we revisit the role of IoT in AMDIs and conclude with avenues for further research.

### 8.3.1 Reflections on the Research and Design Objectives

As described in Chapter 1, the primary objective of this research was to develop a model of AMDIs that improves understanding of asset management through IoT. The fact that IoT adoption improves asset management was not assumed, but was investigated further by means of a systematic literature review and an analysis of three exploratory case studies. "Improvement" of understanding of asset management through IoT was investigated by comparing traditional asset management processes with asset management processes after IoT adoption has taken place. We first looked at how asset managers used IoT to improve the efficiency and effectiveness of their decision-making processes, and listed the potential and achieved benefits of adopting IoT in asset management. However, we were also aware that IoT is a dual technology in that although people have developed the technology, IoT also structures the

way people and organizations think and behave, which then impacts the development and adoption of the technology and so on. Therefore we also looked at the potential and experienced unexpected risks of IoT adoption in the asset management organization. We were able to conclude that IoT adoption changes asset management, and that the IoT adoption process in asset management organizations is multi-dimensional. Asset management organizations should therefore be aware of the duality of IoT during the adoption process if the expected benefits are to be fully achieved.

IoT implementations in asset management organizations rarely, if never, occur in a greenfield situation (a situation in which everything is started from scratch), but rather need to be accommodated inside of already existing AMDIs. We therefore needed to enhance our understanding of AMDIs and what is required to be able to accommodate IoT within these infrastructures. With this in mind, our research was directed to the development of a model of AMDIs which improved understanding of asset management through IoT. Because improving understanding asset management through IoT is a "wicked" problem, we could only hope to satisfice the problem through the design of the model. As such, it was logical to employ the Design Science approach in our research and in the development of the model.

The design objective follows the research objective closely, although there are semantic differences in that the design objective was, essentially, to design a model (of AMDIs which improves understanding of asset management through IoT), whereas the research objective was to improve understanding of asset management through IoT. In this way a successful model design achieves both the design objective and the research objective.

In order to design the model, we needed to understand the elements of AMDIs and their behaviors when faced by IoT adoption, and we needed to be able to facilitate communication of the model between stakeholders in the asset management organization. We took the view that AMDIs are CAS and listed the elements and behaviors of AMDIs from that perspective. These elements and behaviors were identified from the combination of a systematic literature review and the analysis of three exploratory case studies. We found that elements of AMDIs included: components, data governance and environments. Behaviors of AMDIs included: dynamism, connectivity, adaptation and emergence. The AMDI model was evaluated by means of three test case studies. The results of the test case studies were analyzed against the criteria for model validity

and the success of the model in enhancing our understanding of the AMDI landscape and its success in facilitating communication.

We were able to conclude that the model was valid and that it did indeed enhance our understanding of asset management through IoT and facilitate communication. As such, we argue that the model achieved both the research and design objectives.

### 8.3.2 Reflections on the Scientific Contribution

IoT adoption introduces unexpected changes within asset management organizations. In this research we applied Duality of Technology theory (Orlikowski, 1992) to asset management through IoT, and confirmed its dual nature. Second, we acknowledged the complexity of AMDIs and confirmed the necessity of viewing AMDIs as CAS when introducing new technologies such as IoT. Confirming the duality of technology theory and the applicability of CAS theory, meant that we were able to develop a model of AMDIs which provides actionable insights into previously unforeseen changes within asset management through IoT, helping asset managers to take appropriate action before being confronted by changes which were unexpected. The important scientific contributions of this research are discussed below.

1. *Confirmation of the duality of IoT shows that adoption of IoT in asset management is multi-dimensional, being influenced by factors within several dimensions, meaning that asset managers can and should address people and organizational changes parallel to the implementation of IoT technology.*

Many studies on adoption of new technologies such as IoT tend to focus on a single dimension such as organizational factors, as organizational factors tend to be deemed to be primary determinants of innovation adoption in organizations (Subramanian & Nilakanta, 1996). However, a major contribution of this research is to show that asset management through IoT is multi-dimensional, being influenced by factors within several dimensions including: environmental; organizational readiness; technical adoption characteristics; and people. As such the AMDI model designed in this research provides insight into the salient factors of each dimension and their relative explanatory power on asset management through IoT. For example, this research is the first to demonstrate that, within the context of our case studies, it is inefficient to exert a hierarchical control over AMDIs and that a more organic organizational structure should be considered when implementing asset

management through IoT. The research also shows that along with organizational changes, people changes such as developing knowledge on IoT and data science are also essential. Furthermore, there needs to be a close fit with the cultural and political environments if asset management through IoT is to be successful.

2. *The duality of IoT means that asset management through IoT can introduce both expected and unexpected changes to asset management which can lead to many benefits, but also unexpected risks. Understanding the nature of these benefits and risks means that asset managers are able to take appropriate mitigating actions.*

The belief within many asset management organizations is that IoT can be used for a variety of purposes within asset management and can provide many benefits to asset management, but much of the current literature describes only potential uses and expected benefits of IoT without providing real world evidence. As such, this research contributes to the body of literature by providing a systematic review of literature and evidence of attained benefits for asset management organizations through real world examples and case studies, as well as a systematic listing of uses of IoT data in asset management organizations. Similarly, risks of IoT adoption in asset management are often only described in terms of possible risks or barriers. Again, this research has contributed to the body of literature through means of a systematic review of risks of IoT adoption in asset management as well as providing real world evidence of these risks and how organizations have managed these risks. This research has shown how the interconnectivity of risks and benefits have affected asset management and shows how IoT adoption both enables and constrains asset management processes. This dual influence had not yet been recognized in studies that attempt to determine whether IoT adoption has "positive" or "negative" effects on asset management. Orlikowski's (1992) duality of technology framework allowed us to recognize that IoT necessarily has both restricting and enabling implications for asset management. As such, this research has extended the body of knowledge on duality of technology theory by investigating the factors which determine the dominant implication. This research fills the need to address the potentially unanticipated impacts of asset management through IoT (Neisse et al., 2016) and investigates the impact of IoT on asset management in a systematic manner (Haller et al., 2009).

3. *Confirmation of the complexity of AMDIs reflects the necessity of approaching AMDIs as CAS when introducing new technologies.*

This research has been driven by the recent phenomenon of asset management through IoT and the subsequent disruptions. The research focuses primarily on the use of IoT within asset management with particular regard to how IoT can be accommodated within existing AMDIs. There has been little research on AMDIs and this research is the first to confirm the complexity of AMDIs and describe their components, schema and behaviors in terms of CAS. This research shows that elements of AMDIs are sets of system physicalities. Furthermore, the research determines that behaviors of the AMDI are the distinctive collection of functions and operations that make AMDI behavior unique. The elements and behaviors together make AMDIs different from other systems. Few researchers have made the distinction that AMDIs are CAS when defining characteristics of data infrastructures, and there have been a number of calls for attention to this topic (Grus et al., 2010; M. Janssen & Kuk, 2006). As such, this research contributes to the literature on CAS theory by describing the characteristics of AMDIs as CAS in terms of elements and behaviors. Using a CAS lens has helped us to identify and better understand the key characteristics of AMDIs necessary for their functioning and dealing with change.

4. *Identifying and describing data governance as the schema of AMDIs means that the rules governing the changes introduced by asset management through IoT can be better understood.*

This research has shown that in seeking to adapt to changing circumstances, asset managers develop rules that anticipate the consequences of certain responses. This research is the first to investigate these rules in the asset management domain and is the first to research how these rules affect the asset management organization and how they are interpreted as data governance, identifying data governance as embodying the schema of AMDIs. As such, this research shows that data governance defines how the components of AMDIs (data, technology, agents) interact. This research is the first to describe data governance in asset management organizations, and demonstrates that although there is no “one-size-fits-all” solution for data governance, the research shows that it is possible to develop a single framework for data governance implementation in asset management organizations of different sizes and at differing levels.

### 8.3.3 Reflections on the Societal Contribution

As designers, we also wish to be able to exercise a positive influence on the development of AMDIs. Not only do we try to understand how AMDIs are affected by IoT adoption, but we also desire to improve understanding of asset management through IoT. Large-scale data gathering and analytics are quickly becoming a new frontier of competitive differentiation (Herder et al., 2011), and this research has shown that asset management organizations are increasingly looking to data to drive their asset management decision making processes, managed within AMDIs. IoT provides new sources of data, derived from continuously monitoring a wide range of things within a variety of situations, but this research has shown that integrating IoT into existing AMDIs is a complex undertaking and organizations require tools to mitigate risk in IoT adoption. This research has investigated conditions and factors for achieving benefits and suggests approaches to reduce the risks that IoT adoption imposes, providing asset management organizations with a powerful tool in the form of an AMDI model to be able to develop successful strategies when implementing IoT. The important societal contributions of this research are discussed below.

1. *This research provides asset managers with pre-described conditions and factors for effective and sustainable asset management through IoT.*

IoT solutions in the asset management domain are physically constructed by asset managers in an asset management context, and result from the ongoing interaction of human choices and institutional contexts. As such, the research shows that adopting IoT and integrating IoT data into existing AMDIs introduces unexpected risks which cause AMDIs to adapt and evolve in unexpected ways. This research provides asset managers with pre-described conditions and factors for effective and sustainable development of AMDIs which asset managers can use to their advantage when moving to adopt IoT in their primary processes. The research derives a model of AMDIs for sustainable asset management through IoT, outlining principles and guidelines for implementing data governance in asset management organizations. The research demonstrates that the inherent complexity of adopting a data-driven approach to asset management requires an effective data governance strategy to ensure data quality, manage expectations, build trust and integrate IoT data in AMDIs.

2. *This research provides structured guidelines as to how changes to the AMDI wrought by IoT adoption may be coordinated through data governance.*

Because there is a dependence on interactions between elements of AMDIs, the ability to organize these elements and coordinate their interactions is essential to asset management through IoT. As such, this research provides structured guidelines as to how IoT adoption may be organized through data governance. As asset management organizations gradually become more and more data driven, the need for formalized data governance is becoming more and more apparent. Having high-quality, secure data that is compliant with relevant laws and directives and is privacy aware is a precondition for analyzing and using IoT data and for guaranteeing the value of the data. However, comprehensive quality standards and quality assessment methods for IoT data remain immature. For asset managers to be able to trust data driven decisions, there needs to be increased quality of the data generated by IoT connected devices, and the integrity of the data needs to guaranteed as it moves through the enterprise to decision makers. IoT data has to be trusted. The quality of data driven decisions can only be as good as the quality of the data being used to make those decisions, and ensuring that data is managed properly and of sufficient quality is vital to asset management through IoT.

3. *The results of this research suggest that cultural change and organizational change should take place parallel to the technical changes for asset management through IoT.*

The democratization of computing technology through the increasing diversity, availability and affordability of sensors and small computing devices has meant that more and more asset management organizations are looking to adopt IoT to improve their primary processes. However, for IoT to become truly transformative in the asset management environment a cultural shift as well as technical shift is required. Asset management organizations need to change their cultures so that asset management through IoT becomes ingrained throughout organization rather than being lost in departmental silos. Data needs to be integrated and analyzed for actionable insight, so that the right decisions can be made by the right people at the right time across many complex asset management processes. We therefore suggest that more asset managers need to become more at home with data and data analytics. In order for

an asset management organization to become truly data driven, asset managers need to feel comfortable working with data. On the other hand, data analysts and data analysts also need to become more at home with asset management processes so that irregularities in the data may be more easily identifiable as attributable to activities and events in the primary processes, making the data easier to understand.

4. *This research provides asset managers with a powerful ontological tool for configuring organizational specific AMDIs and assessing change requirements for asset management through IoT.*

The AMDI model described in this research provides a point of reference for designers to extract system specifications for IoT adoption in asset management organizations, providing a method to document the IoT system for future reference. For example, the results of the exploratory case studies and literature review identified a number of socio-political and external factors that can influence asset management through IoT. The AMDI model described in this research includes the cultural, physical and political environments within the asset management sector and enhances our understanding of socio-political IoT system requirements in an asset management environment by highlighting the need for access to high levels of financial and other resources.

### 8.3.4 Reflections on IoT in Asset Management

IoT is introducing a paradigm shift as to how data is accumulated in asset management. The increasingly large amounts of sensors being introduced in infrastructure networks and their networking provide asset management organizations with a central nervous system whereby the infrastructure may be managed from multiple perspectives. For example, just as with the human central nervous system, the need for extremities to react quickly to incidents has introduced the concept of edge computing, in which an automatic response is generated at source. Just as our internal bodily functions are automatically regulated, so can IoT provide the signals required for basic functioning of assets to be automated. Furthermore, just as with the human body, the need to learn from experiences has also meant that more and more, data from sensors is also being transported and stored in central registries where trend analysis and machine learning can allow asset management to become predictive instead of reactive. Just as we now eat healthier food, take vaccines and do sport to maintain a healthy lifestyle and prevent sickness and injury based on knowledge we have gained by studying the signals

we receive from our bodies, IoT data will allow asset management to design cost effective, preventative measures which prolong asset lifetimes and improve efficiency and effectiveness of services. Sufficient data points which provide usable measurements and which are connected to descriptions of assets, combined with advances in data science and machine learning will provide asset management with a central nervous system that drives automated response where possible and directed response where necessary.

As such, the IoT paradigm shift is driven less by technology and more by the data it produces. Although advances in technology are required to further enable IoT development, the value proposition of IoT adoption remains with the data being produced and the information that asset management organizations are able to extract from the data. Data produced at source may trigger automated response, and later be converted to information from which the organization may learn and develop the knowledge required to continually improve their asset management processes. Sensors and technology may be replaced, but the data remains. Just as the human brain manages the signals it receives, learning to manage and use IoT data without creating noise is essential.

### 8.3.5 Reflections on the Future of Asset Management

As IoT develops and is further adopted by asset management organizations, it is not unthinkable that many asset management functions will gradually become more and more automated as infrastructures increasingly need to balance functionality and cost. This can create a fear that asset managers will become obsolete in the future as artificial intelligence begins to take over. This may be so for essential functions which can and should be automated, but it is not expected that artificial intelligence will take over completely. People will always be an integral part of the AMDI as it is not the infrastructure that has needs, but people, the ultimate users of the infrastructure. Infrastructure exists to fulfill our changing needs, and it is only people who may decide what our own needs are. We therefore suggest that the roles currently performed by people in asset management will change substantially as IoT becomes more pervasive, but the need for human influence will remain. More operational decision-making roles may be greatly reduced as IoT data allows for automation of reactive processes based on data, however, asset management people roles will become more strategic as artificial intelligence based on trend data presents strategic options. Strategic decisions, although data driven, will always be influenced by

developments and external interests such as politics which may fall out of the scope of the local AMDI. As such, it may be unwise to rely on artificial intelligence to make strategic decisions for us. This being noted, being data-driven does also mean that asset managers need to become more data aware in order to adapt to changing knowledge requirements for their functions. It is clear that data analysis skills are becoming more and more important to the asset management process, and asset managers can no longer rely on the IT function to provide the knowledge necessary. Successful asset managers should and will develop more applied data analysis and machine learning skills.

### 8.3.6 Reflections on Model Driven Adoption of IoT in Asset Management

Although IoT produces large amounts of data, it would be incorrect to suggest that IoT data is structureless. Using models to drive architecture in the development of AMDIs ensures that asset management organizations develop a complete overview of their data landscapes so that they may achieve a complete view of their infrastructures. Allowing the wild spread of sensor related data can result in the overdevelopment of data in some areas and the underdevelopment in others. In areas where IoT does not have a presence, the view of the asset infrastructure may become splintered, and conversely and perversely, areas where sensors are overpopulated may muddy the waters. Model driven architecture also ensures that the development of the system architecture is agnostic, being platform independent. This is of vital importance for interoperability and the sharing of data between systems. The development of systems to serve individual functions is becoming untenable as the budgets of IT departments increasingly come under pressure. As such, AMDIs can no longer afford to be process oriented in which each individual process has its own data collection. To continue with the analogy with the human nervous system, asset management organizations can no longer afford to have situations in which the left hand literally has no idea what the right hand is doing. The infrastructure needs to be managed as an integral system, and not as a collection of different systems.

## 8.4 Research Limitations

This section describes the limitations of our study. Research limitations are discussed with regard to taking a constructivist perspective, adopting

the design science approach, the generalization of the findings from the selected cases, and the evaluation of the model using test cases.

### 8.4.1 Taking a Constructivist Perspective

According to (Phillips, 1995), constructivism is to be praised for its emphasis on learners' active participation and the heightened recognition given to the social nature of learning. However, (Liu & Matthews, 2005) believe that the bad side of constructivism lies in its tendency towards epistemological relativism which they believe to be the major challenge that constructivists face. Epistemological relativism is the view that knowledge is relative to time, place, society, etc. and what counts as knowledge depends upon a relationship with one or more of these variables. Duality of Technology theory (Orlikowski, 1992) suggests that IoT will have an effect on asset management and on asset managers themselves. How organizations react to innovations such as IoT can often be culturally based. As such, we must acknowledge that the study was conducted wholly in the Netherlands, and focused particularly on government and semi-government organizations. Furthermore, two of the test cases occurred within the same organization, namely, Stedin, and one of the test cases occurred in within an organization which had been used within the exploratory cases, namely Rijkswaterstaat. Future research should therefore take into account the fact that language and cultural differences were not assimilated into the model. This places question marks against generalization in an international environment or in private organizations.

### 8.4.2 Limitations of Case Study Research

According to (Zainal, 2017) the case study method often receives criticism in terms of its lack of robustness as a research tool, and the design of case studies is therefore of paramount importance. Case study research is an approach to studying a social phenomenon and rests on the assumption that the case being studied is typical of cases of a certain type so that generalizations may be made that will be applicable to other cases of the same type. Also, the interaction of the researcher with the phenomenon under study means that the possibility of researcher bias is always present, as is the potential for differing interpretations. These restrictions can lead to a limited potential for generalization and have particular implications for data collection and analysis methods and for research outcomes (Cavaye, 1996).

Furthermore, although case study research is useful as a means of studying information systems development and use in the field, there can be practical difficulties associated with attempting to undertake case studies as a rigorous and effective method of research (Darke et al., 1998). As with all case studies, this research was limited by time and resources, and it is always possible that some information was not uncovered, or incorrectly interpreted, which may affect the overall findings.

## 8.5 Towards an Agenda for IoT AMDI Research

This chapter has highlighted what has been accomplished in this study, and it has also shown that the study has had various unavoidable limitations. Furthermore, this research has brought to light a number of research areas which remain lacking in maturity. Based on the limitations mentioned in section 8.4 of this chapter as well as the identification of research areas lacking in maturity, seven recommendations have been made for further research. The recommendations address limitations of this research as discussed in the previous section. Recommendations 1, 2 and 3 address limitations of the research occurring due to the constructivist perspective, namely generalization limitations with regards to *culture*, *time* and *work area*. Recommendations 4 and 5 address limitations of the research with regards to the use of case study as method, namely the need to investigate in greater detail ways to improve *trust* and *usability* of IoT in asset management. Recommendations 6 and 7 address the need for further development of duality of technology theory and CAS theory as frameworks to further help us understand the digital transition.

*Recommendation 1: Extend and generalize the AMDI model to include potential international, language or business cultural differences.*

The research was conducted wholly in the Netherlands and did not have an international scope. Furthermore, only government and semi-government organizations were included in the case studies. However, we have seen that the environment in which an AMDI is located can have an important influence on the development of the AMDI, especially in the face of a disruptive technology such as IoT. Different cultures may have differing views with regards to risk and how to approach IoT adoption in the face of the risks posed by this technology. Differing cultures may also have varying approaches to organizational change. For example, a

relatively young, private startup with corresponding demographic may be expected to approach the idea of IoT adoption differently to an established organization which is responsible for infrastructures which are critical to the nation. Improvement can be achieved by investigating more case studies in non-similar situations and by involving more stakeholders such as practitioners (mechanics or engineers) working in the primary processes.

For generalization we may consider applying the AMDI model presented in this research not just in the public sector, but also in the private sector and in organizations outside of the Netherlands. Although the AMDI model aims to help asset management organizations in the Dutch public sector, companies managing large scale infrastructure either under contract or privately (such as mines for example) can also consider using it.

As such the first recommendation suggest the extension and generalization of the model in various directions, including international case studies or case studies in the private sector. Our model provides a structure, but the evolutionary characteristic of CAS is that structure can change. Although our model does take evolution and adaption into consideration, more research should be conducted into the evolutionary nature of AMDIs. As such, our second recommendation reads as follows:

*Recommendation 2: Examine the evolving design of the AMDI over time.*

Over the course of the research we were made aware of how the AMDI evolves as it is adopted and used. However, the further evolution of the AMDI was outside the scope of this study. We suggest that future research examines how the design of the AMDI is adapted through the continued interaction of asset managers with IoT technology. This research may help better understand the more behavioral aspects of AMDIs so that asset management organizations may be better placed to anticipate changes to the AMDI and the organization as a whole. As such, the findings may then be used to further improve the AMDI so that further benefits of IoT adoption may be achieved. It would be good to investigate how this AMDI model may be applicable to other domains and where the AMDI model may benefit from experiences in other domains. This leads us to our third recommendation which reads as follows:

*Recommendation 3: Study to which extent the AMDI model is applicable to domains other than asset management.*

All the case studies focused on identifying and testing requirements for the data infrastructure model in asset management, with particular regard to water management, road management and energy grid management. Moreover, the number of cases was limited to one per level. In the first place, some of the requirements may be typical for only for certain domains and perhaps less typical for other domains. Future research is recommended on studying to which extent requirements are specific to certain domains. Furthermore, we expect that the IoT AMDI model may be generalizable to areas other than asset management in the physical infrastructure asset management domain. We recommend investigating in how far the model remains applicable to other types of asset management and other types of IoT data infrastructures. For example, IoT is expected to transform many industries, such as health care and agriculture. We have also seen that evolution is driven by innovation, not only in technology, but also in processes. As such, data governance is becoming increasingly important for ensuring that data provision is aligned with information needs, and that compliance to local and international laws and directives is maintained. This brings us to our fourth recommendation which reads as follows:

*Recommendation 4: Investigate and extend the data governance framework to include useable guidelines and tooling for ensuring sustainable alignment to business needs and compliance to local and international laws and directives.*

It is through data governance that data can be organized and managed for sustainable use. Effective data governance enables those charged with protecting their asset management organizations to manage the data, documents, and records they will need to ensure compliance to laws and directives. Unorganized and unmanaged data impede organizational performance and create legal risks when critical data go missing or when data leaks occur, and decisions based on poor quality data can have devastating consequences. Efforts to apply data governance from the executive level downwards have not always been successful due to a lack of organizational interest in an initiative that seems distant from the primary processes. Furthermore, politics surrounding data governance such as deciding on accountabilities have also created obstacles which require design solutions to help asset management organizations overcome foreseeable obstacles. As such, we have noticed that governance design involves more than only executive management support. Data managers, as well as all staff working in the

asset management process and supporting staff that manage the involved data systems must be engaged in order to ensure compliancy and data integrity throughout the data management process. Ensuring data integrity also means ensuring protection from malevolent outside influences or ill-advised practices. As such, the data governance framework should be extended to investigate means of ensuring data security throughout the AMDI in the face of evolving technologies so that practitioners may have access to tools that ensure sustainable data protection throughout the infrastructure. This leads us to our fifth recommendation which reads as follows:

*Recommendation 5: Investigate and extend the data governance framework to include tools for improving trust by ensuring the sustainable security and integrity of the route that the data follows from the IoT device to the information consumer.*

IoT has potential to improve asset management, generate efficiencies in asset management organizations, increase safety, save costs and create value for asset management organizations. It has also changed the way people think about asset related business models and how to best support those. AMDIs are often purpose-built to solve specific asset management requirements, but the duality of IoT leads to changes to asset management organizations which we need to better understand. Duality of Technology theory has shown us that changes can occur to the organization and to people in the organization, which, in turn, lead to changes in the technology. With the advent of machine learning, artificial intelligence and technological agents such as bots and robots, it is unclear how these new sorts of agents will be affected by IoT adoption. This leads us to recommendation 6, which reads as follows:

*Recommendation 6: extend the theory of duality of technology by investigating the influence of IoT adoption on artificial agents and their roles in organizations.*

As mentioned above, IoT adoption introduces changes to many facets of the data infrastructure, as organizations are increasingly faced with a digital transition. This change may occur gradually or suddenly, but always comes paired with adaptation and evolution. More knowledge is needed to understand the various facets and relationships occurring within data infrastructures as complex systems in order to be able to better anticipate how change may occur and where. As such, we need to

better understand the complexity of data infrastructures and their embodiment as CAS. This leads us to recommendation 7, which reads as follows:

*Recommendation 7: extend CAS theory for data infrastructures by investigating how data infrastructures may adapt and evolve during the digital transition.*

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# Summary

Modern economies are supported by large public utility infrastructures. As such, the proper management and maintenance of infrastructure is vital to economic prosperity. These infrastructures consist of networks of assets and are often managed by organizations using an asset management approach. Asset management is a discipline for managing infrastructure assets. Asset management as a process is highly dependent on large amounts of data from which relevant information can be created. More and more, new technologies such as IoT are becoming available and are being adopted by asset managers to provide the data required to acquire the necessary insights in a timely fashion. IoT is a network of physical objects that can communicate digitally over the internet. However, adopting IoT in asset management organizations (organizations tasked with managing and maintaining public utility infrastructure assets) is a complex undertaking. Design solutions that improve understanding of asset management through IoT are needed to ensure that asset managers continue to be supplied with the right information at the right time. Our objective was to develop a model of AMDIs that improves understanding of asset management through IoT.

The underlying premise of this research is derived from the *Duality of Technology theory* (Orlikowski, 1992) suggesting that IoT will introduce unexpected changes to asset management and we confirm the dual nature of IoT in asset management. Second, we acknowledge the complexity of AMDIs and view AMDIs as CAS. AMDIs are shared, evolving, heterogeneous, set of resources capable of providing the data and context required to fulfil the information requirements of asset management organizations. On the basis of the insights provided by duality of technology theory and CAS theory, we develop a model of AMDIs which improves understanding of asset management through IoT. For example, the model confirms the belief that hierarchical organizations are less equipped to adopt asset management through IoT and that a more network-based, organic organizational structure provides a better fit for asset management through IoT as suggested by Damanpour & Gopalakrishnan (1998).

In order to achieve our objective we developed a framework of research questions which reads as follows:

1. How can IoT improve asset management?
2. What are the elements and behaviors of AMDIs that enable asset management through IoT?
3. What are the elements of data governance in AMDIs that enable asset management through IoT?
4. What does a model of an AMDI that accommodates IoT look like?
5. How does the AMDI model improve understanding of asset management through IoT?

"Improving" means making something better. As such, answering these questions required a strong design component. We therefore adopted the Design Science approach as suggested by Hevner (2007). The Design Science approach requires multiple iterations within three mutually interdependent "cycles". Building the knowledge base and developing the design requirements occur in the rigor cycle and relevance cycles respectively. We therefore adopted a two-pronged approach to answering questions 1, 2 and 3 which provided us with the knowledge base and requirements necessary to be able to answer question 4 through the design and build of the model and to be able to test the model and by doing so answer question 5. Our two-pronged approach to answering questions 1, 2 and 3 was:

1. The development of the knowledge base through a systematic literature review.
2. The development of the knowledge base through exploratory case studies.

During the design cycle, as more and more knowledge and requirements became available through the literature review and the exploratory case studies, we were able to add more elements to the model design. Once we had reached a point of saturation and the model was considered to be sufficient, answering question 4, we tested the model by means of test case studies in which we tested the usability and usefulness of the model. By doing so we also tested our design proposals, answering question 5 and thus achieving the research objective.

The literature review follows the method proposed by Webster & Watson (2002) and attempts to systematically analyze and synthesize literature and advance the knowledge base of AMDI research. As mentioned above, the literature review partly answers research questions 1, 2 and 3.

This research uses case study as principle research method, following the method proposed by Yin (2009). Two forms of case study are used in this research: exploratory case studies; and test case studies. Exploratory case studies are used to fill gaps in the knowledge base and

complete the answers to research questions 1, 2 and 3 (completing the relevance and rigor cycles), and to provide requirements for the build of the model and the answer to research question 4. The test case studies were used to evaluate the model and answer research question 5 (completing the design cycle). The table below summarizes the cases selected for this research.

Table S-1: Case studies selected for this research

| Case Study | Organization | Level | Case Type |
|---|---|---|---|
| LMW | RWS | National | Exploratory |
| Ground Water Management | Municipality of Rotterdam | Regional | Exploratory |
| BOS | Water Authority Delfland | Local | Exploratory |
| WIM | RWS | National | Test |
| Smart Meters | Stedin | Regional | Test |
| Hoog Dalem | Stedin | Local | Test |

In exploratory case studies, Yin (2009) suggests using a theoretical framework during the investigation. We therefore confirmed the applicability of duality of technology (Orlikowski, 1992) theory to asset management through IoT, and the necessity of approaching asset management as CAS, using these theories as lenses to describe the exploratory case studies from varying perspectives. By doing so we were able to uncover a number of previously undocumented insights into asset management through IoT including:

Duality of Technology as theoretical framework:

- Benefits and unexpected risks of IoT for asset management organizations as a product of human agency
- Benefits and unexpected risks of IoT for asset management organizations as a medium of human agency
- Organizational conditions for interaction with IoT in asset management
- Organizational consequences of interaction with IoT in asset management

CAS as theoretical framework:

- Essential components of AMDIs
- Characteristic behaviors of AMDIs
- Concepts of the role of Data Governance in AMDIs
- Effects of physical, social and political environments on AMDIs

As such, the results of the literature review and the exploratory case studies meant that we were able to answer research questions 1, 2 and 3 in the following ways. Firstly, in order to answer research question 1, we split it into three sub-questions. Research question 1a asked: *How can IoT be used to improve asset management?* We can summarize the answer to this question as:

- IoT improves performance measurement of infrastructure service
- IoT improves perception of infrastructure service
- IoT improves improvement processes of infrastructure service

As important as it was to discover how IoT is being used in asset management, and how IoT has changed traditional asset management practices, we also needed to understand if these changes had to led to provided benefits for asset management. Therefore, we asked the sub-question: 1b: *What are the expected benefits of asset management through IoT*? We can summarize the answer to this question as:

- Technology changes: benefits of IoT as a product of human agency
- People changes: benefits of IoT as a medium of human agency
- Organizational changes: Benefits related to organizational conditions of interaction with IoT
- Organizational changes: benefits related to organizational consequences of interaction with IoT

However, knowing the dual nature of asset management through IoT meant that we also needed to understand the unexpected risks brought about by IoT adoption in asset management. Therefore we asked the sub-question: 1c: *What are the risks posed by asset management through IoT*? We can summarize the answer to this question as:

- Technology changes: Risks related to IoT as a product of human agency
- People changes: Risks related to IoT as a medium of human agency
- Organizational changes: Risks related to organizational conditions of interaction with IoT
- Organizational changes: Risks related to organizational consequences of interaction with IoT

As such, the complete answer to Research Question 1 is the collection of answers to questions 1a, 1b and 1c. Studying the uses, benefits and risks of IoT adoption helped us understand its dual nature and what changes to asset management and asset management organizations may be expected due to IoT adoption. It became clear that IoT adoption in asset

management is highly complex and modelling AMDIs which can accommodate IoT adoption requires a CAS approach. We therefore applied CAS theory to the exploratory case studies which gave us a framework in which to define the elements of AMDIs and their behaviors. We split question 2 into two parts. The first part, question 2a was: *What are the elements of AMDIs that enable asset management through IoT*? We can summarize the answer to this question as follows:

- Components: Data, Technology, Agents
- Data Governance
- Environments: Political, Cultural, Physical

The second part of question 2, question 2b was: 2b: *What are the behaviors of AMDIs that enable asset management through IoT*? We can summarize the answer to this question as follows:

- Dynamism
- Connectivity
- Adaptation
- Emergence

As such, the complete answer to research question 2 is the collection of answers to questions 2a and 2b.

Following the CAS framework we were aware that components and agents operating within the AMDI construct formal and informal rules which govern decision-making and interactions. The so-called, "schema" of CAS. During the exploratory case studies we were able to identify this schema for AMDIs as being data governance. However, we also became quickly aware that the knowledge base of data governance is extremely thin, and especially so in the context of asset management. Therefore, as mentioned above, we asked our third research question as follows: *What are the elements of data governance in AMDIs that enable asset management through IoT*? We can summarize the answer to this question as follows:

- Organizational capability
- Alignment
- Compliance
- Clarification

The insights uncovered by the exploratory case studies led us to three main design propositions which helped drive the theoretical contribution of the model design. The propositions look at each of the elements within the AMDI, namely the components (human and technological), data governance (which governs the decision-making and interactions), and the influence of the varying types of environments in which the AMDI occurs. These propositions were:

1. Configuring the elements of AMDIs to accommodate IoT adoption improves understanding of asset management through IoT.
2. Implementing data governance improves understanding of asset management through IoT.
3. Configuring AMDIs to accommodate cultural, physical and political environments improves understanding of asset management through IoT.

The design requirements gathered during the exploratory case studies helped drive the practical contribution of the model design. During the exploratory case studies we were able to analytically derive 30 requirements from the results of research questions 1, 2 and 3 and complete the answer to research question 4 which asks: *What does a model of an AMDI that accommodates IoT look like*? Of the 30 requirements there were:

- 6 stakeholder requirements facilitating communication of IoT system details between stakeholders in an asset management organization.
- 6 system requirements dealing with component implementation of IoT.
- 8 system requirements dealing with data governance implementation.
- 6 system requirements dealing with managing environmental effects.
- 4 system requirements dealing with behavior of the AMDI.

Based on the design propositions (as theoretical contribution) and requirements (as practical contribution) we derived 30 design principles which gave direction to the design of the model, of which:

- 6 were principles which facilitate communication of the AMDI design.
- 24 were principles which enhance our understanding of the AMDI design.

Further, to complete the answer to research question 4 we are able to say that the model uses W3C specifications and addresses four specific concepts, namely:

- Classes (general things) in the many domains of interest.
- The relationships that can exist among things.
- The properties (or attributes) those things may have.
- Constraints on relationships between the classes and their properties.

Also, the model employs a combination of object-oriented and agent-oriented perspectives, and follows the linked open data approach. We were able to extend the model where necessary to include existing ontologies.

Once we had reached a level of saturation in the design, and the build phase of the model was considered complete, as no new information was forthcoming, we proceeded to test the model by means of test case studies, in answer to research question 5 which asks: *How does the AMDI model improve understanding of asset management through IoT*? The model was tested based on its usability and usefulness. Although usefulness is often seen as a characteristic of usability, we paid special attention to usefulness, as by means of this test we wanted to test the robustness of the design propositions.

With regards to usability, we first looked at the effectiveness of the model by considering whether the model was complete, or by contrast, overcomplicated. We were able to conclude that no extraneous classes could be found nor could we find individuals which did not fit in the existing classes. Secondly we looked at the effectiveness of the model by monitoring how quickly it took to complete the model for specific situations and by looking at the "learnability" of the model, in other words, how much time it took for users to learn how to use the model. We also looked at the users response to using the model and the level of satisfaction of using the model. We were able to conclude that the model could be completed in an acceptable amount of time with minimal explanation. Also, we were able to note that most users were relatively happy with how the model performed. As such, we were able to conclude that the model met the technical usability criteria.

With regards to the usefulness of the model our focus lay with the testing of our design propositions. Design proposition 1 was tested by looking to see if the model provided actionable insights into the influence of people and technology on asset management through IoT. The AMDI model showed that agents have a particularly large influence on asset management through IoT. As such, asset management organizations should enable asset management through IoT by developing awareness of the benefits of IoT and providing opportunities for personal development in this area. For example, both Stedin and RWS identify a lack of data science skills as major barriers in the adoption of IoT in asset management and both organizations have initiated training programs designed to improve data awareness and analytics skills within the organization. The AMDI model also showed that data governance should ensure that data is aligned with the needs of the business, including

ensuring that data meets the necessary quality requirements. For example, the level of accuracy and timeliness of the data being generated by the WIM is essential for traffic warden to be able to react in a timely fashion and with confidence in the results.

Design proposition 2 was tested by looking to see if the model provided actionable insights into the influence of data governance on asset management through IoT. With regards to the test cases, both RWS and Stedin have well-structured processes to incorporate new technologies and have developed strong relationships with knowledge institutes. For example, WIM was developed by RWS in cooperation with technical universities and private knowledge institutions. As such, application of the model shows that high levels of networks between cooperating agents is an enabling factor for asset management through IoT. Also, the AMDI model showed that management support positively influences asset management through IoT in the form of "championship" and leadership promotion. For example, the executive management at the Department of Central Information Management at RWS played an important role in championing the use of WIM data for asset management, as did the Director of Strategy and the Chief Data Officer at Stedin with regards to Smart Meter data.

Design proposition 3 was tested by looking to see if the model provided actionable insights into the influence of socio-political environments on asset management through IoT. According to Damanpour & Schneider (2006), urbanization and development around an adopting organization have a positive association, as organizations in urban areas tend to have easier access to service providers and face more diverse and complex environments than those in rural areas (Boyne, Gould-Williams, Law, & Walker, 2005). However, the AMDI model showed that this may not necessarily be the case, as the cases occur in largely rural areas. However, we did notice that all the cases have a high level of environmental complexity and are relatively wealthy, having access to high levels of financial and other resources. According to Daft, Murphy, & Willmott (2010), greater environmental complexity leads to more numerous, specialized and interconnected organizational parts, stimulating higher rates of innovation and change, and Damanpour & Schneider (2006) show that resources also provide local governments of wealthier communities with a greater ability to prepare organizational and community members for implementing the new programs or services. As such, application of the AMDI model shows that organizational wealth and complexity may have a larger influence on IoT adoption in asset management organizations that other factors such as urbanization.

As seen in the discussion above, we were able to conclude that the asset management model did meet the criteria of providing actionable insights for asset managers with regards to IoT adoption in each of the propositions, and we therefore argue that the model can be considered "useful".

Once we had concluded the tests, we then took some distance from the research in order to reflect on the findings, and draw conclusions from the evidence presented by the research. We began our reflections by drawing conclusions on how the process of IoT adoption affects asset management and asset management organizations, and then drawing conclusions on the desired end-state of IoT adoption affects asset management and asset management organizations.

Applying Duality of Technology theory with regards to research question 1 and the process of IoT adoption, helped us to conclude that, within the context of our case studies, the goodness-of-fit between IoT and the asset management organization is critical for the successful adoption of IoT in asset management organizations. For example, the importance of people as agents within the AMDI suggests that fostering trust in IoT is critical for the improvement of asset management through successful adoption of IoT in asset management organizations. Furthermore, we also argue that management support in the form of "championship" and leadership promotion can positively influence agents, and have a positive effect on IoT adoption in asset management organizations. As such, we were able to observe a change in traditional asset management methods, and, with regards to research question 1 and the end-state of IoT adoption, we were able to conclude that, within the context of the cases studies, it is inefficient to exert a hierarchical control over AMDIs when adopting IoT in asset management. This is because asset managers need to develop trust in the IoT system before accepting the results and recommendations provided by the system and allowing themselves to be data-driven. For example, application of the model in the test cases showed that staff felt most empowered when working in a self-managing format with management setting priorities.

The application of CAS theory with regards to research question 2 and the process of IoT adoption, helped us to conclude that, within the context of the case studies, environmental complexity in combination with access to sufficient resources, rather than urbanization, stimulates higher rates of IoT adoption in asset management organizations. Furthermore, not only the physical environment is important, but also the political and cultural climates fit is important in the enablement of IoT adoption in asset management organizations. As such, we can conclude that aligning IoT

solutions with existing asset management environments has a positive influence on IoT adoption in asset management organizations. With regards to research question 2 and the end-state of IoT adoption, we were able to conclude that, within the context of the cases studies, a lack of awareness of the possibilities and pitfalls of IoT can have a negative influence on the adoption of IoT in asset management. We therefore argue that asset managers need to improve their knowledge and level of awareness of IoT to enable the adoption of IoT in asset management organizations, and that organized social networks within and outside an asset management positively influence the adoption of IoT in asset management organizations.

With regards to research question 3 and the process of IoT adoption, we were able to conclude that, within the context of the case studies, the importance of data provenance for IoT infrastructures and the persisting requirement for manual intervention suggests the need for instituting strong data governance procedures which align inter-functional teams behind a common goal. The idea of inter-functional teams suggests a change to traditional asset management organizational structures, and so, with regards to research question 3 and the end-state of asset management through IoT, we were able to conclude that, within the context of the cases studies, enabling asset management through IoT requires that asset management organizations adopt a more organic organizational structure in which an environment of trust is created for inter-functional teams.

Conclusions relating to the first three research questions helped shape the design of the AMDI model, but we were also able to take some distance from the design process and draw conclusions about the model itself and the design process. As such, with regards to research question 4 and the process of IoT adoption, we were able to conclude that, cross-over modelling improves our ability to model and understand AMDIs as complex systems. The application of CAS theory helped us understand how the components of AMDIs interact. As such, with regards to the end-state, we were able to conclude that relationships among the functional elements of AMDIs help us understand what the AMDI model looks like. Furthermore, these AMDI constructs also help us understand how the model improves understanding of asset management through IoT by facilitating early detection and correction of system development errors, as well as helping us understand the social impact of asset management through IoT.

Research question 5 asks *how does the AMDI model improve understanding of asset management through IoT?* Our tests of the model

in the test case studies demonstrated that the model improves understanding of asset management through IoT by providing insights into previously unforeseen changes to asset management and the asset management organization. We can conclude that the model improves understanding of asset management through IoT by:

*Process related conclusions*:

- Providing a point of reference for designers to extract system specifications for IoT adoption in asset management, providing a method to document the IoT system for future reference.
- Showing that asset management through IoT does not randomly occur, but rather occurs as a result of specific needs and interventions.
- Highlighting the need for access to high levels of financial and other resources.
- Communicating the need for a fit between the political and cultural climate before implementation can be successfully realized.
- Providing insight into the relationships between actors in the asset management organization and how these relationships influence asset management through IoT.

*End-state related conclusions:*

- Providing insight into uses, benefits and risks of asset management through IoT.
- Facilitating communication of IoT system details between stakeholders in an asset management environment and provides a means for collaboration between agents in the asset management organization.
- Enhancing our understanding of people requirements for asset management through IoT.

Of course, whilst drawing these conclusions, we were aware that our research has limitations which the reader should be aware of. For example, taking a constructivist perspective meant that the research is limited in terms of epistemological relativism. For example, the study was conducted wholly in the Netherlands and focused only on government and semi-government organizations. As such, generalization in an international or commercial environment should be approached with caution due to the fact that the potential impacts of language, as well as national and commercial business culture were not assimilated into the model. Furthermore, the research method chosen, case study, also has inherent limitations which should not be ignored. Using the case study

method means that one should be aware of the potential for differing interpretations of the data as well as the possibility that potential, important information may not have been discovered, meaning that there exists the potential that analysis was made on the basis of incomplete or potentially misleading data.

We therefore made a number of recommendations for further research which include addressing potential limitations due to epistemological relativism by extending the model to include language, and national or business cultural differences as well as examining the evolution of the AMDI over time. Addressing the limitations of case study, we also recommend investigating and extending the data governance framework to include useable guidelines and tooling for ensuring sustainable alignment to business needs and compliance to local and international laws and directives, as well including useable tools for ensuring the sustainable security and integrity of the route that the data follows from the IoT device to the information consumer.

# Appendices

## Appendix A: Summary of the AMDI model classes

Table B-1: The classes of the AMDI model

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| AMDI | | IsDynamic<br>AdaptsToChangeFrom<br>IsConnectedThrough<br>EmergentBehaviorIn-ResponseTo | Represents the AMDI: the sum of all its elements. |
| Component | AMDI | Enables<br>Constrains | Represents the sum of the components of the AMDI. |
| Agent | Component | Uses<br>Role<br>DataOwner<br>Influences<br>DataSteward<br>DataManager | An agent (e.g. person, group, software or physical artifact). Autonomous, goal driven entities that are able to communicate with other agents and whose behavior is the consequence of their (1) observations, their (2) knowledge and their (3) interactions with other agents. |
| Robot | Agent | Uses<br>Influences | A machine— especially one programmable by a computer— capable of carrying out a complex series of actions automatically |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| Data | Component | DataOwner<br>DataSteward<br>Aligns<br>Models<br>Directs<br>Enables<br>Controls<br>Regulates<br>Constrains<br>Influences<br>Describes<br>EnablesPerformance-Analysis<br>EnablesExpectation-Management<br>EnablesInfrastructure-ServiceProcesses | Symbols representing measures or descriptions of objects or events. |
| Metadata (=DGClarification) | Data | Describes | A description of a data entity. |
| Domain-Independent-Metadata | Metadata | Describes | Includes generic descriptions such as the creator or modifier of data as well as authorization and lineage information related to the data. |
| DomainSpecific-Metadata | Metadata | Describes | Provides a set of mappings from a representation language to agreed-upon concepts in the real world. |
| PhysicalMetadata | Metadata | Describes | Includes information about the physical storage of data. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| UserMetadata | Metadata | Describes | Includes annotations that users may associate with data items or collections; such annotations can, for example, capture user preferences and usage history. Stores user attributes (such as user preferences) that do not impact a user's core functionality. |
| Registration | Data | Registers | Symbols representing measures or descriptions of objects or events. |
| Description | Registration | Describes | Symbols representing descriptions of objects or events. |
| Identification | Description | Identifies | Symbols used to uniquely identify an object or event. |
| Measurement | Registration | Measures | Symbols representing measures of objects or events. |
| Technology | Component | Influences EnablesPerformance-Analysis EnablesExpectation-Management EnablesInfrastructure-ServiceProcesses | The collection of Information Technology (IT) artifacts, hardware and software, used in the production of data or services or in the accomplishment of objectives, such as data analysis or data management. |
| Hardware | Technology | EnableCompute ConstrainCompute | The physical parts or components of an IT system. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| Intelligent-Processing | Hardware | Processes<br>Decides | A variety of intelligent computing technology, used to achieve intelligent decision-making and control |
| Perception | Hardware | Perceives | Includes hardware used for the acquisition of observations or measurements by using perception, acquisition and measurement technology such as RFID, two-dimensional code and sensors, etc. |
| Transmission | Hardware | Transmits | Includes hardware that ensures that the objects have access to information networks and can realize reliable information interaction and sharing through communications networks. |
| Software | Technology | Instructs<br>EnablesData-Management<br>ConstrainsData-Management | A set of instructions or programs instructing a computer to do specific tasks. Software is a generic term used to describe computer programs. |
| Algorithm | Software | EnablesIntelligent-Processing<br>Constrains-Intelligent-Processing | A process or set of rules to be followed in calculations. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| Application | Software | EnablesIntelligent-Processing Constrains-Intelligent-Processing | An application is any program, or group of programs, that is designed for the end user. |
| Platform | Software | Enables-Transmission Constrains-Transmission EnablesPerception Constrains-Perception | A platform is a group of technologies that are used as a base upon which applications are developed. |
| DataGovernance | AMDI | Enables Constrains | Represents the Schema of the asset management data infrastructure: shared rules which are embodied by norms, values, beliefs, and assumptions |
| DGAlignment | Data-Governance | Aligns | Objects used to align business needs with data. |
| Business-Requirement | DGAlignment | BRRequires | Specifications which once delivered, provide value. |
| Shareholder-Requirement | Business-Requirement | BRRequires | Clusters of IoT "use" in asset management. |
| System-Requirement | Business-Requirement | BRRequires | Clusters of functional and behavioral requirements. |
| Functional-Requirement | System-Requirement | BRRequires | Clusters of component requirements. |
| NonFunctional-Requirement | System-Requirement | BRRequires | Clusters of behavioral requirements. |
| BusinessRule | DGAlignment | Constrains Defines | Rules that define or constrain some aspect of business. |
| DGClarification (=Metadata) | Data-Governance | Clarifies | Objects used to ensure clarification of Data |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| DataModel | DGClarification | Models | an abstract model that organizes elements of data and standardizes how they relate to one another and to properties of the real world entities. |
| Lineage | DGClarification | Maintains-Descendency | The path that a data attribute travels between systems, and the alterations made during that journey. |
| Standard | DGClarification | Standardizes | Objects that provide requirements, specifications, guidelines or characteristics that can be used consistently to ensure that materials, products, processes and services are fit for their purpose. |
| DGCompliance | Data-Governance | Constrains | Objects which ensure compliancy of data to policy, laws and directives. |
| DataAudit | DGCompliance | Controls | A formal and official verification of quality and conformance to requirements, regulations, standards and/or guidelines. |
| DataPolicy | DGCompliance | Regulates | An organization's set of data management objects designed to assist business administration and protect company assets. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| DataStrategy | DGCompliance | Directs | A business plan for leveraging and enterprise's data assets to maximum advantage. |
| DGOrganizational-Capability | Data-Governance | Organizes Structures | Objects required to ensure organization of data governance in a particular organization. |
| Coordination-Mechanism | DGOrganization | Coordinates | The coordination mechanism(s) used to manage data in an organization. |
| Contracting | Coordination-Mechanism | Contracts | A coordination mechanism that divides activities into subtasks that can be performed by specialist agents. |
| Feedback | Coordination-Mechanism | Signals | A coordination mechanism that enables a process to use its own output to adjust its inputs and subprocesses. |
| Planning | Coordination-Mechanism | Plans | A coordination mechanism that creates a detailed proposal for doing or achieving something. |
| SelfOrganization | Coordination-Mechanism | Organizes | A coordination mechanism whereby processes are able to adjust and adapt themselves to both external and internal influences. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| DataManagement-Process | Organization | Manages | The business function that develops and executes plans, policies, practices, and projects that acquire, control, protect, deliver and enhance the value of data. |
| DataArchitecture-Management | Data-Management-Process | Designs | Objects used for the design and construction of an integrated data resource that is business driven, based on real-world subjects as perceived by the organization, and implemented into appropriate business environments. |
| DataIntegration-And-Interoperability-Management | Data-Management-Process | Integrates | Objects that determine how data is selected, transformed and flows across databases. |
| DataQuality Management | DataManagement -Process | Controls | Objects that ensure that the development effort will result in the desired product. |
| DataSecurity-Management | DataManagement -Process | Secures | Objects that prevent unauthorized access to a database and its data, and to applications that have authorized access to databases. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| DataStorage-And-Operations-Management | DataManagement -Process | Store<br>Create<br>Read<br>Update<br>Delete | Objects that provide support from data acquisition to purging. |
| Data-WarehousingAnd-Business-Intelligence-Management | DataManagement -Process | Analyzes<br>Presents | Operational, administrative and control objects that provide access to Business Intelligence data and support to knowledge workers engaged in reporting, query and analysis. |
| DocumentAnd-Content-Management | DataManagement -Process | Store | Object that manage data found outside of standard structured databases. |
| Metadata-Management | DataManagement -Process | Create<br>Control<br>Integrates<br>Analyzes | Objects that create, control, integrate, access and analyze metadata repositories to allow for easier access. |
| ReferenceAnd-MasterData-Management | DataManagement -Process | Controls | Objects that ensure consistency with a 'golden version' of data values. |
| Environment | AMDI | Enables<br>Constrains | Represents the total surroundings or conditions in which the AMDI occurs. |
| Cultural-Environment | Environment | Enables<br>Constrains | Objects that represent a set of beliefs, practices, customs and behaviors that are found to be common to all agents operating within the AMDI. |

| Class Name | Subclass Of | (Domain) Properties Include: | Description |
|---|---|---|---|
| Physical-Environment | Environment | Enables<br>Constrains | The sum of the tangible objects in the area within which the AMDI occurs |
| Political-Environment | Environment | Enables<br>Constrains | Governing objects which affect the operations of the AMDI. |

# Appendix B: The Object Properties of the AMDI Model

Table B-2: The object properties of the AMDI model

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| AdaptsTo-Change-From | | AMDI | Component Environment Data-Governance | Indicates that the object is capable of adapting to changes occurring in other classes in its range. |
| Aligns | | DG-Alignment | AMDI | Indicates that data meets the necessary requirements to align with the requirements of the business. |
| Analyzes | | Metadata-Management Algorithm DataWare-housingAnd-Business-Intelligence | Data | Indicates that the object is capable of analyzing data. |
| Clarifies | | DG-Clarification | AMDI Data | Indicates that the object clarifies the entity. |
| Maintains-Descendency | Clarifies | Lineage | Data | Indicates that the object maintains lineage |
| Models | Clarifies | Data-Modelling-AndDesign DataModel | AMDI | Indicates that the object is capable of modelling. |
| Standardizes | Clarifies | Standard | AMDI | Indicates that the object provides a standard. |

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| Constrains | | Cultural-Environment DG-Compliancy Data-Governance Political-Environment Component BusinessRule Software | Data-Governance Component Environment AMDI | Indicates that the object constrains activities. |
| Constrains-Compute | Constrains | Hardware | Software Data | Indicates that the class constrains computation. |
| Controls | Constrains | DataQuality-Management Metadata-Management Reference-And Masterdata-Management DataAudit | AMDI Data | Indicates that the object monitors compliancy to norms, policies, laws and regulations. |
| Regulates | Constrains | DataPolicy | AMDI | Defines the actions required to comply to norms, policies, laws and regulations. |
| Decides | | Intelligent-Processing | AMDI | Indicates that the object is capable of making an intelligent decision |
| Describes | | Metadata Description | AMDI Data Registration Metadata Measuremen t | Indicates that the object describes another object or activity. |
| Directs | | Data-Strategy | AMDI | Indicates that the property gives direction. |
| Emergent-BehaviorIn-ResponseTo | | AMDI | Component Data-Governance Environment | Indicates that this object displays emergent behavior in response to changes in other objects. |

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| Enables | | Data-Governance Software Environment Component | AMDI Environment Data-Governance Component | Indicates that the object is capable of enabling another object. |
| Enable-Compute | Enables | Hardware | Data | Indicates that the class enables computation. |
| Enables-Expectation-Management | Enables | Data Technology Agent | Agent | Indicates that the object is capable of enabling expectation management. |
| Enables-Infrastructure-Service-Processes | | Data Technology | AMDI | Indicates that the object is capable of managing connected data resources. |
| Enables-Coordination-OfProcesses | Enables-Infrastructure Service-Processes | Data Technology | AMDI | Indicates that the object is capable of enabling coordination of processes. |
| Enables-Industrial-Automation | Enables-Infrastructure Service-Processes | Data Technology | AMDI | Indicates that the object is capable of enabling industrial automation. |
| EnablesInfra-Usage | Enables-Infrastructure Service-Processes | Data Technology | AMDI | Indicates that the object is capable of enabling usage of infrastructure. |
| EnablesPolicy-Development | Enables-Infrastructure Service-Processes | Data Technology | AMDI | Indicates that the object is capable of enabling policy development. |
| Enables-Performance-Analysis | Enables-Infrastructure Service-Processes | Data Technology | AMDI | Indicates that the object is capable of enabling performance analysis. |
| EnablesData-Management | Enables | Software | Data | Indicates that the object is capable of enabling data management processes. |
| Enables-Perception | EnablesData-Management | Platform | Data | Indicates that the object is capable of enabling perception processes. |

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| Enables-Processing | EnablesData-Management | Application Algorithm | Data | Indicates that the object is capable of enabling data processing. |
| Enables-Transmission | EnablesData-Management | Platform | Data | Indicates that the object is capable of enabling transmission of data. |
| Identifies | | Identification | AMDI | Indicates the object or event which is identified. |
| Influences | | Environment Component Data-Governance | AMDI | Indicates that this object has an influence on the objects in its range. |
| Instructs | | Software | Hardware | Indicates that the object is capable of instructing a computer to perform a specific task. |
| IsConnected-Through | | AMDI | Environment Component Data-Governance | Indicates that this object displays connectivity. |
| IsDynamic | | AMDI | Environment Component Data-Governance | Indicates that this object is capable of changing dynamically. |
| Manages | | Data-Management Process | Data | Indicates the object is capable of managing data. |
| Create | Manages | Metadata-Management DataStorage And-Operations-Management | Data | Indicates that the object is capable of creating data. |
| Delete | Manages | DataStorage And-Operations-Management | Data | Indicates that the object is capable of deleting data. |
| Designs | Manages | DataArchitecture-Management | Data | Indicates that the object is capable of managing architecture design. |

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| Integrates | Manages | Data-Integration-AndInter-operability-Management | Data | Indicates the object is capable of managing data integration. |
| Presents | Manages | DataWare-Housing AndBusiness Intelligence-Management | Data | Indicates that the object is capable of presenting data. |
| Read | Manages | DataStorage And-Operations-Management | Data | Indicates that the object is capable of reading data. |
| Secures | Manages | DataSecurity Management | Data | Indicates that the object is capable of providing data security. |
| Store | Manages | Document-AndContent-Management DataStorage And-Operations-Management | Data | Indicates that the object is capable of storing data. |
| Update | Manages | DataStorage And-Operations-Management | Data | Indicates that the object is capable of updating data. |
| Measures | | Measure-ment | AMDI | Indicates that the object is capable of measuring another object or event. |
| Organizes | | DG-Organization Self-Organization | AMDI | Indicates that this object defines the rules for organizing the AMDI. |
| Coordinates | Organizes | DG-Organization CooridinationMechanism | AMDI | Indicates that the object determines the coordination mechanism used to coordinate interaction with other objects. |
| Contracts | Coordinates | Contracting | AMDI | Indicates that the object is capable of contracting. |

| Object Property Name | Subclass Of | Domain Classes | Range Classes | Description |
|---|---|---|---|---|
| Plans | Coordinates | Planning | AMDI | Indicates that the object is capable of planning. |
| Signals | Coordinates | Feedback | AMDI | Indicates that the object is capable of providing feedback. |
| DataOwner | Foaf:Role | Agent | Data | Indicates that the agent has accountability for ensuring data is properly managed. |
| DataSteward | Foaf:Role | Agent | Data | Indicates that the agent is responsible for ensuring data is properly managed. |
| Structures | | DG-Organization | Agent | Indicates that this object structures the process or organization. |
| Perceives | | Perception | Data | Indicates that the object is capable of perceiving the world and transforming the perception into data. |
| Processes | | Intelligent-Processing | Data | Indicates that the object is capable of processing data for intelligent decision-making. |
| Registers | | Registration | Data | Indicates that the object is capable of registering data. |
| Transmits | | Transmission | Data | Indicates that the object is capable of transmitting data. |
| Uses | | Agent | Data Technology | Indicates that this object uses objects in its range for a particular purpose. |

# Appendix C: Comparison of the Test Cases on Class and Individual Levels

Table C-1: Comparison of the test cases on class and individual levels

| AMDI Class Name | Individuals of WIM | Individuals of Smart Meter | Individuals of Hoog Dalem |
|---|---|---|---|
| Group | AssetManager<br>EnforcementAgency | End-user<br>Energy Supplier<br>GridManager | Aggregator<br>Prosument<br>Supplier |
| Organization | Police<br>RWS<br>Transport Inspectorate | Stedin<br>Tennet | Stedin<br>Tennet |
| OrganizationalUnit | CIV Data<br>CIV IT<br>WVL | GSA<br>IT<br>MeterAssetManage ment<br>MeterKast&-Aansluiting<br>SmartData<br>Telecom | MeterKast&-Aansluiting<br>SmartData<br>Strategie |
| Person | DataAnalyst<br>RoadManager<br>TrafficInspector<br>TrafficOfficer | AssetManager<br>DataAnalyst<br>HomeOwner | AssetManager<br>DataAnalyst<br>HomeOwner |
| Robot | | | SmartAppliance |
| Domain-Independent-Metadata | | | HashStore |
| DomainSpecific-Metadata | OGC_Technical Metadata | ReadOutSymbols | MessageStore |
| PhysicalMetadata | OGC_MetadataInfor mation | | AGRPortfolio<br>PlanBoard |
| UserMetadata | NGR_WIM | SMUserInstructions | CommonReference |
| Description | KemlerPlate | MeterConfiguration-Cat1 | Day-aheadMarketPrices<br>PVLoadForecast |
| Identification | NumberPlate | MeterID | MeterID |
| Measurement | Length<br>Speed<br>Weight | 15minvalues-Cat5<br>ElectraMeterReadin gs-Cat3<br>ElectricGridManage ment-Cat2 | Congestion-PointLimits<br>FlexPotential<br>PVLoad<br>UncontrolledLoad |

| AMDI Class Name | Individuals of WIM | Individuals of Smart Meter | Individuals of Hoog Dalem |
|---|---|---|---|
| | | GasMeterReadings-Cat4<br>HourValuesGas-Cat6 | |
| Intelligent-Processing | Central Analysis<br>WebPortal<br>WIMDataAccess System | Splunk Dashboards | WebPortal |
| Perception | Camera<br>InductionLoop<br>LoadSensor | SmartMeter | SmartMeter |
| Transmission | VIC-Net | CDMA<br>GPRS | CDMA<br>GPRS |
| Algorithm | BI_reports | Dashboard algorithms | PBC Layer |
| Application | CognosBI<br>Winfrabase | MeterFrontEnd | WorkFlowLayer |
| Platform | WIDAS | Splunk | ServiceLayer |
| Functional-Requirement | WIMFunctional-Specs<br>Overloading-Enforcement | DSMR-Functional<br>Handleiding_SM | Implementation-Guidelines<br>UseCase-Descriptions |
| NonFunctional-Requirement | WIMSystem Requirements | DSMR-Technical | InstallationManual |
| BusinessRule | ConfigurationRules | NEDU-user profiles<br>NEDU-market profiles | Libraries in use<br>NamingConventions<br>Prerequisites<br>Glossary<br>Interface-Descriptions |
| DataModel | OGC_NGR-Datamodel | NEDU-data profiles | UDIDataStructure&Messages |
| Lineage | DataManagementProcessDescriptions | P4_score | DataManagement-ProcessDescriptions |
| Standard | OGC Standards | NEDU | USEF |
| DataAudit | TNO Reports | ACM<br>GDPR | LevelsofCompliancy<br>PrivacybyDesign |
| DataPolicy | ProjectReports<br>ServiceDescriptions | NEDU-process-improvements&-innovation<br>PIA | MessageTransport&Descriptions |

| AMDI Class Name | Individuals of WIM | Individuals of Smart Meter | Individuals of Hoog Dalem |
|---|---|---|---|
| DataStrategy | i-Strategie RWS | Stedin_Data-Strategie | USEF Framework Specs |
| Contracting | SystemFocused-Contract-Management | SM Aansluiting-contract | InterActorMessage-Flows |
| DataArchitecture-Management | WIM SystemArchitecture ServiceDefinitions | DSMR Architecture NEDU profile definitions | USEF Reference-Architecture USEFComponentModels USEFLayeredViews |
| DataIntegration-And-Interoperability-Management | WIDAS system design | DSMR_integration architecture | CommonInboundMessageRoutingFlow CommonInbound-MessageFlow CommonOutbound MessageFlow CommonProcess-Flow FileLoggerFlow HashCheckFlow MessageIDCheck-Flow PBCInvocationFlow ResolveParticipant-Flow |
| DataQuality Management | 2stage QualityAssurance | P4_score | DataIntegrityGuidelines |
| DataSecurity-Management | VICNet security and firewall | DSMR_Security Specs | USEFPrivacySecurityGuideline USEFSecurityLayer |
| DataStorageAnd-Operations-Management | BI database | SCADA Management | DataStoreSchemas |
| DataWarehousingAndBusiness-Intelligence-Management | BI Warehouse | BW on Hana | |
| DocumentAnd-Content-Management | PDF-ECM | SMOOC_fileshare StedinIntranet | MessageCatalog |
| Metadata-Management | OGC_NGR | StedinIntranet | Interface-Descriptions |
| ReferenceAnd-MasterData-Management | RDW database | StedinERP | DataManagement-Guidelines |

| AMDI Class Name | Individuals of WIM | Individuals of Smart Meter | Individuals of Hoog Dalem |
|---|---|---|---|
| Cultural-Environment | Open and Inclusive Respect For Privacy | Healthy Suspicion Inclusiveness | EchtHoogDalem – "a nice place to live" |
| Physical-Environment | Highway | Personal Homes | Suburban |
| Political-Environment | Strict Enforcement Laws | Strict Data Protection Laws | Well defined rules |

# Appendix D: Case Study Protocol

The case study protocol follows the template as suggested by Yin (2009, pp. 84–86). Yin (2009) suggests that the protocol is a major way of increasing the reliability of the research and advises including four sections to the protocol: A. An overview of the study; B. Data collection procedures; C. Data collection questions; and D. A guide for the case study report.

## Section A: Overview of the Case Study

With regards to section A of the protocol, Table D-1 below summarizes the sub-parts of the protocol and how they are dealt with in this research.

Table D-1: Section A of the protocol and how the sub-parts are dealt with in this research

| **Sub-part of the Protocol** | **How it is reported in this research** |
|---|---|
| 1. Change Record | The research report is versioned. Significant versions summarize main updates and reasons for these. |
| 2. Background | The background of the research is reported in Chapter 1 |
| 2a. identify previous research on the topic | 2a. Previous research is discussed in the literature review in Chapter 3 and in the introduction in Chapter 1. |
| 2b. define the main research question being addressed | 2b. The main research question is described in Chapter 1 |
| 2.c identify any additional research questions that will be addressed | 2. All research questions are described and discussed in Chapter 1 |
| 3. Theoretical framework for the case study | The theoretical frameworks used in the exploratory case studies: CAS theory and Duality of Technology theory, are discussed in Chapter 4. |
| 4. Role of the protocol in guiding the case study | The protocol was used as a standardized agenda for our line of inquiry, providing an overview of the research, the process to be followed in the research and guiding the line of questioning. |

## Section B: Data Collection Procedures

With regards to section B of the protocol, Table D-2 below summarizes the sub-parts of the protocol and how they are dealt with in this research.

Table D-2:Section B of the protocol and how the sub-parts are dealt with in this research

| **Sub-part of the Protocol** | **How it is reported in this research** |
|---|---|
| 5. Names of contact persons for doing field work | Names and contact details of contact persons are not made public. Due to privacy concerns all names and contact details are protected and will only be released with express permission from the individuals. |
| 6. Data collection plan | The data collection plans are presented in chapters 4 and 7. |
| 7. Data storage plan | All data is stored in a versioned cloud storage facility. The data is warehoused according to source and type. |
| 8. Expected preparation prior to field work | Researchers familiarized themselves with the goal and purpose of the research prior to performing field work. In this research this was done by means of a workshop in which the background and goals were explained and discussed. During the workshop the data collection topics were also discussed and interview techniques were practiced. Junior interviewers were required to observe at least 5 interviews performed by senior interviewers prior to performing independent interviews. |

## Section C: Data Collection Questions

With regards to section C of the protocol, Table D-3 below summarizes the sub-parts of the protocol and how they are dealt with in this research.

Table D-3: Section C of the protocol and how the sub-parts are dealt with in this research

| **Sub-part of the Protocol** | **How it is reported in this research** |
|---|---|
| 9. Data Collection Questions | The following topics were listed as being of importance for the interview. Specific topics to be discussed were identified for specific interviewees as not all interviewees were expected to be proficient in all the topics:<br><br>1. Describe the IoT implementation in as much detail as possible, including:<br>- Technology<br>- Processes<br>- Relevant people and departments<br>2. How is the IoT implementation used?<br>3. Who uses the IoT implementation?<br>4. What does the architecture of the IoT implementation look like?<br>5. What is data governance to you? |

| Sub-part of the Protocol | How it is reported in this research |
|---|---|
| | 6. How is ownership of data organized?<br>7. What does data quality mean to you?<br>8. What data is created by the IoT implementation?<br>9. What is this data used for?<br>10. How is data quality monitored?<br>11. Are there legal constraints to which the use of data must be compliant?<br>12. How is compliance assured?<br>13. Who are the main stakeholders?<br>14. What is the role of the government in ensuring the IoT implementation is successful?<br>15. What were the main benefits of adopting the IoT system?<br>16. What were the main barriers or learning points during the adoption of the IoT system?<br>17. How did the idea for the IoT system come about?<br>18. What were the original goals of the IoT implementation?<br>19. In what ways was the IoT implementation innovative?<br>20. How was the IoT implementation funded?<br><br>The interviews were unstructured and interviewers were encouraged to delve further after the initial response. As such, not all questions were dealt with in each interview, but rather specific areas were dealt with based on the target interviewee. |

## Section D: Guide for the Case Study Report

With regards to section D of the protocol, Table D-4 below summarizes the sub-parts of the protocol and how they are dealt with in this research.

Table D-4: Section D of the protocol and how the sub-parts are dealt with in this research

| Sub-part of the Protocol | How it is reported in this research |
|---|---|
| 10. Audiences for the report and stylistic preferences | The main audience for the report include both the scientific community as well as people working in asset management organizations. As such, a report style was adopted in which the asset management community were able to read and understand the report, whilst also acknowledging the formality of the scientific format. |
| 11. Innovativeness of the IoT adoption | The report looks at why IoT was adopted in the asset management organization, and what the organization expected to gain from the adoption of IoT as opposed to pre-IoT adoption practices. The study also looks at the hurdles the adoption needed to overcome – what made the adoption difficult and why was it different to other projects? |

| Sub-part of the Protocol | How it is reported in this research |
|---|---|
| 12. Outcomes of the IoT adoption to date | The report looks at the results of the IoT adoption – has it achieved its goals? And also how these results are measured and monitored. |
| 13. Asset management context and history pertaining to traditional practices | The report looks at how asset management was conducted before IoT adoption – does IoT improve the practice, if so how, and is it accepted? |
| 14. Exhibits to be developed: chronology of events, logic model, references to relevant documents | The report presents and discusses these exhibits in Chapters 4 and 7. |

# Appendix E: Publications by the author

## Journal Articles

- Brous, P., Janssen, M., Herder, P. (2018). Internet of Things Adoption for Reconfiguring Decision-Making Processes in Asset Management. Business Process Management Journal. Special Issue: "Reconfiguring business processes in the new political and technological landscape".
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# Curriculum Vitae

Paul Allan Brous was born on the 10th of September 1976 in Chiredzi, Zimbabwe. After graduating from Peterhouse, Zimbabwe with Cambridge A-Levels in 1994, he received a bursary from the Independent Schools of Zimbabwe to study Education at Rhodes University, South Africa, graduating in 1998 with a Bachelor of Arts degree and a University diploma in Primary Education. After four years of teaching at Springvale House, Zimbabwe, he immigrated to the Netherlands in 2003, teaching at Arnhem International School, Arnhem and De Blijberg International School, Rotterdam for three years before joining Grontmij, De Bilt, as consultant and project manager in 2007. During this period he completed the GIMA Master of Science program, graduating with a Master of Science in Geographic Information Systems and Applications in 2009. In 2009 Paul joined Rijkswaterstaat, Delft as data manager and project manager. During his time at Rijkswaterstaat Paul worked in a number of positions, eventually filling the role of Enterprise Data Architect from 2014. Also during this time, Paul became a researcher at the Faculty of Technology, Policy and Management of Delft University of Technology. During his time at TU Delft, Paul gave a number of guest lectures, taught classes in ICT, and supervised Masters students. His research was published in several international journals and he presented his research at international conferences in the USA, Portugal, Hong Kong, the Netherlands, Wales and Greece. In 2016 Paul joined Unit4, Utrecht as Global Lead Data Architect and in 2017 he joined Stedin, Rotterdam as Lead Enterprise Data Architect. Currently Paul is owner and Director of Legend Data Management, a company specializing in consultancy with regards to data management, data architecture, data governance and data quality management.