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Feedback technology & behavioral change

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SIMULATING CO-DIFFUSION OF INNOVATIONS: FEEDBACK TECHNOLOGY & BEHAVIORAL CHANGE

Proefschrift

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aan de Technische Universiteit Delft,
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voorzitter van het College voor Promoties,
in het openbaar te verdedigen op donderdag 23 maart 2017 om 15:00 uur

door

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There is nothing noble in being superior to your fellow man;
true nobility is being superior to your former self.

Ernest Hemingway

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I would like to share the intriguing feeling that my colleagues, friends, and family might have contributed more to this thesis than I did. For some reason, an academic title is often attributed to one individual. Paradoxically, this individual's success is a collective achievement. This is why I would like to express my gratitude to all those who supported this work.

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[1] This is not a lie.

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CONTENTS

SUMMARY

This thesis explores how behavior-changing feedback devices can reduce energy demand of heating residential buildings.

Greenhouse gas emissions of residential buildings need to be reduced as soon as possible, which can be achieved by changing heating behavior. Because heating residential building consumes a large share of energy in the EU, their energy-efficiency needs to be increased. Due to the long service time of buildings, the pressing reduction of emissions also needs to include existing buildings. Large-scale adoption of conservation behavior is a promising approach towards this aim. Behavior change could save about 20% percent of domestically consumed energy. Additionally, change in behavior is widely applicable in the built environment, resource- and cost-efficient, and of low capital intensity.

Behavior-changing feedback devices are a useful approach to change energy-consumption behavior. They monitor and present (e.g. on in-home displays) how residents are consuming energy. Such feedback showed to nudge householders to save an average of 7%–15% of energy.

The future impact of these devices on a societal scale is of great interest. Commonly, feedback devices are assessed by observing their impact within individual households. Whereas this direct impact is important, the overall impact of devices at wider adoption is highly relevant, too. It is worthwhile to know *how quickly* different social groups would adopt feedback devices, and how this could support societal trends towards conservation behavior. Because this impact has not been realized yet, this thesis assesses this potential looking forward.

This thesis assumes a perspective of innovation diffusion. Due to their novelty, behavior-changing feedback devices can be framed as innovations. It is of interest to analyze the spreading of these devices from their first adopters to a potential larger user base. In addition to this *technology diffusion*, the conservation behavior incentivized by feedback devices can also diffuse. According to Social Learning Theory, social contacts often imitate each others' behavior, which makes behavior spread. This *behavior diffusion* has repeatedly been observed empirically. For the case of behavior-changing feedback devices, these two diffusions of technology and behavior are interlinked via the behavior change that feedback devices exceed on their users. As feedback devices diffuse, behavior change of their users may thus positively affect the diffusion of conservation behavior.

Agent-based modeling is suited for simulating this *co-diffusion of technology and behavior*. Simulation can directly incorporate existing knowledge of the impact of feedback devices in field tests. This knowledge on this impact can then be scaled up by simulation. Doing so can further make use of theoretical knowledge on the mechanisms of the diffusions of household devices and conservation behavior. However, the future diffusion of feedback devices is not a given, but subject to inherent uncertainty.

Therefore, simulation shows the consequences of what happens if a feedback device will diffuse successfully. The potential impact of this technology can thus be analyzed in 'what-if' scenarios. Agent-based modeling is particularly useful for all these tasks. It has the combined advantages of an actor-based perspective, its capability to infer emergent system behavior from these micro-level definitions, and disaggregated modeling of consumer decisions.

Unfortunately, this disaggregation also makes agent-based modeling somewhat cumbersome, which is what that thesis aims to improve. Despite its usefulness, agent-based modeling is presently relatively demanding in labor and programming skills. To reduce these costs, this thesis applies agent-based modeling with the aim to also make it quicker and more accessible. This is done by automation, which makes modeling more systematic than what is common practice for innovation diffusion models.

Motivated by this, this thesis addresses the following central research question:

How can the impact of behavior-changing feedback devices on energy-consumption behavior be systematically simulated?

First, a framework of co-diffusion of technology and behavior was developed and implemented in an abstract agent-based model. This served to explore via which mechanisms feedback devices create an impact in a large-scale social system. To realize the applied model, two previously published models on behavior diffusion and technology diffusion were linked by the effect of an abstract feedback device. This assumed the diffusion of a feedback device that nudges its adopters to lower their heating temperature. Additionally, this created conservation behavior then diffuses via behavior diffusion.

Simulation revealed two mechanisms via which behavior-changing feedback devices create an impact. First, behavior diffusion distributed the behavior change incentivized by feedback devices from adopters to non-adopters of devices. Second, this similarity increased the speed of overall behavior change. Due to these mechanisms, feedback effect and behavior diffusion interacted positively. The indicated relevance of the combined co-diffusion of technology and behavior confirmed the value of the used framework.

Next, analysis was made empirical. This made use of rich empirical data in the case city Bottrop (Germany) and of a case technology that nudges its users to ventilate their homes energy efficiently. The feedback effect component of the co-diffusion framework was modeled based on data from field tests of this feedback device. Likewise, also modeling the diffusion of energy-efficient ventilation behavior was calibrated with empirical data.

This empirically-grounded model allowed measuring the relative importance of the simulated processes. Results suggested that up to 46% of the overall impact from the case technology was caused by behavior diffusion. This confirmed the previously indicated relevance of including behavior diffusion in assessing the impact of feedback

devices.

Based on the previously developed empirically-based model, impacts of policies were analyzed. This includes measures of supporting device adoption that the literature suggested to be successful. Selected policies included raising awareness, giving away free devices, and lending them out. Each of these marketing strategies was simulated at the same strength (i.e. number of used devices) and scale (i.e. same spatial area and time horizon). These policies were tested by simulating scenarios of their implementation. Their impact was then compared regarding effectiveness and cost-efficiency.

Results showed that lending out devices was particularly effective, whereas creating sole awareness of them was most cost-efficient. Overall, the impact of feedback devices was sensitive to policy choices. This highlighted the need to select the right diffusion strategy when aiming to maximize the impact of feedback devices.

Finally, the methods that were developed during this thesis were standardized and unified in an automation approach. This led to a software prototype that standardizes these methods via automation. This increased automation in the generation of agent-based innovation diffusion models and the assessment of policies. Candidates of innovation diffusion models were thereby varied in structure and parameters to test their plausibility for a given real-world case.

Based on (potentially multiple) plausible models, diffusion policies were assessed for their potential to support device diffusion. Thus, standardizing the modeling process sped it up and made the use of empirical data more systematic. Further, this approach was capable of improving existing models, as well as generating models that were *validated by design*. Combined, this showed the developed automation approach successfully contributes to the method of innovation diffusion modeling.

It can be concluded that impact of feedback devices can successfully be assessed by systematically simulating the co-diffusion of these devices and the behavioral change they create. This relied on four pillars. First, assessment of impact based on developing and simulating the framework of co-diffusion of technology and behavior. This generalized the understanding of the potential impact of feedback devices. Second, the initially abstract analysis was refined by empirical data. Third, this developed empirical-based model allowed to assess the potential for policies to influence the impact of feedback devices. Fourth, automation made assessment of this impact more performant and accessible. Overall, this systematization improves the way agent-based models of innovation diffusion are developed and applied.

SAMENVATTING

Dit proefschrift beschrijft hoe apparaten die feedback geven om gedrag te veranderen de energievraag ter verwarming van huizen kunnen verlagen.

Broeikasgasemissies van woonhuizen moeten zo snel mogelijk worden gereduceerd. Deze reductie kan worden bereikt door het gedrag omtrent het verwarmen te veranderen. Omdat het verwarmen van woonhuizen een groot aandeel heeft in het energieverbruik in de EU moet de energie-efficiëntie worden verhoogd. Vanwege de lange levensduur van gebouwen vereist de urgente behoefte aan emissiereductie ook het beschouwen van bestaande gebouwen. Het op grote schaal adopteren van besparend gedrag is een kansrijke aanpak om dit doel te bereiken. Gedragsverandering kan ongeveer 20% van de door huishoudens geconsumeerde energie besparen. Daarnaast is gedragsverandering breed toepasbaar in de gebouwde omgeving, is het grondstoffen- en kostenefficiënt en het brengt weinig kapitaalkosten met zich mee.

Het gebruik van apparaten die feedback geven om gedrag te veranderen vormt een bruikbare aanpak voor het veranderen van gedrag rondom energieconsumptie. Ze monitoren en brengen de mate van energieconsumptie in beeld (bijvoorbeeld op schermen in huizen). Het is bekend dat feedback op die manier bewoners aanzet tot energiebesparing van 7%–15%.

De toekomstige impact op maatschappelijke schaal is interessant. Het is gebruikelijk om apparaten die feedback geven om gedrag te veranderen te beoordelen door naar het effect te kijken op individuele huishoudens. Ondanks dat deze directe impact belangrijk is, moet voor het bepalen van de totale impact ook worden gekeken naar de impact van deze apparaten bij verdergaande adoptie. Het is nuttig om te weten *hoe snel* verschillende sociale groepen deze apparaten willen adopteren en hoe dit de maatschappelijke trends in grootschalige energiebesparing kan ondersteunen. In dit proefschrift wordt dat potentieel verkend, omdat deze impact tot op heden nog niet is gerealiseerd.

Dit proefschrift gaat uit van een innovatie-diffusieperspectief. Omdat apparaten die feedback geven om gedrag te veranderen nieuw zijn, worden ze gezien als een innovatie. Het is interessant om de verspreiding van deze apparaten te analyseren, van de eerste adopters naar een mogelijk grotere gebruikersgroep. Naast de *diffusie van de technologie*, kan ook het besparende gedrag, dat wordt gestimuleerd als gevolg hiervan, verspreiden. Volgens de sociale leertheorie komt het regelmatig voor dat sociale contacten elkaars gedrag imiteren. Dit maakt het mogelijk dat bepaald gedrag zelf verspreidt. Deze zogenaamde *diffusie van gedrag* is herhaaldelijk empirisch geobserveerd. Voor apparaten die feedback geven om gedrag te veranderen worden de diffusieprocessen van technologie en gedrag gekoppeld door middel van de gedragsverandering die de apparaten aanmoedigen. Daarnaast kan, bij de verspreiding van apparaten die feedback geven om gedrag te veranderen, de gedragsverandering van hun gebruikers een positief effect hebben op de diffusie van energiebesparend gedrag.

Agentgebaseerd modelleren is geschikt voor de simulatie van deze processen: de *co-diffusie van technologie en gedrag*. Simulatie kan daarbij bestaande kennis uit praktijktests integreren met die over impact van apparaten die feedback geven om gedrag te veranderen. Deze kennis over hun impact kan in simulaties worden opgeschaald. Tevens kan gebruik gemaakt worden van de theoretische kennis over de mechanismes die een rol spelen bij de diffusie van huishoudelijke apparaten en gedrag rondom besparing. Desalniettemin spelen inherente onzekerheden een rol in de toekomstige diffusie van deze apparaten. Dat betekent dat simulatie in staat is om de gevolgen te laten zien van apparaten die feedback geven om gedrag te veranderen onder de aanname van een succesvolle diffusie. De potentiele impact van deze technologie wordt dan bestudeerd onder 'wat als' scenario's. Agentgebaseerd modelleren is bij uitstek geschikt voor deze taken, omdat het de voordelen van een actorperspectief combineert met het vermogen systeemgedrag af te leiden uit het modelleren van individuele consumentenbeslissingen die worden gedefinieerd op microschaal. Bij agentgebaseerd modelleren kan het modelleren van individuele beslissingen omslachtig zijn. Dit proefschrift heeft als doel daar verbetering in aan te brengen. Agentgebaseerd modelleren is, ondanks haar nut, tot nu toe relatief bewerkelijk en vereist veel programmeervaardigheden. Om de hieruit volgende kosten te verlagen, wordt in dit proefschrift agentgebaseerd modelleren toegepast met als doel het sneller en meer toegankelijk te maken. Daartoe wordt automatisering toegepast: dit maakt het modelleren voor innovatie-diffusiemodellen meer systematisch dan tot op heden gebruikelijk is.

Dit was de aanleiding voor de volgende hoofdonderzoeksvraag:

Hoe kan de impact van apparaten die feedback geven om gedrag omtrent energieconsumptie te veranderen systematisch worden gesimuleerd?

Allereerst is een raamwerk van de co-diffusie van technologie en gedrag ontwikkeld. Dat raamwerk werd geïmplementeerd in een theoretisch agentgebaseerd model. Dit had als doel om de mechanismes te verkennen waarmee feedbackapparaten impact bewerkstellingen in een grootschalig sociaal systeem. Om het model te ontwikkelen zijn twee eerder gepubliceerde modellen over diffusie van gedrag en technologie aan elkaar gekoppeld; het effect van een theoretisch feedbackapparaat werd daarin gemodelleerd. De diffusie van een feedbackapparaat werd aangenomen die gebruikers aanzet tot het verlagen van de temperatuur van hun verwarming. Dit besparende gedrag kon verspreiden via het proces van gedragsdiffusie.

Simulaties hebben twee mechanismes in beeld gebracht waarmee deze feedbackapparaten invloed uitoefenen. Het eerste mechanisme brengt de gedragsdiffusie van feedbackapparaten van adopters naar niet-adopters. Het tweede mechanisme was een positief effect op de snelheid van de gedragsdiffusie als geheel. Het gevolg van deze mechanismes is een positieve interactie van het effect van feedback en gedragsdiffusie. De bepaalde relevantie van het gecombineerd bestuderen van de diffusie van technologie en gedrag bevestigt de waarde van het ontwikkelde raamwerk.

De tweede stap was een empirische analyse met rijke data afkomstig uit de stad Bottrop (Duitsland) en een technologiecasus die gebruikers aanmoedigt tot het energie-efficiënt ventileren van huizen. Het feedbackeffect uit het co-diffusieraamwerk werd gemodelleerd op basis van data van praktijktests van dit feedbackapparaat. Ook de diffusie van energie-efficiënt ventilatiegedrag werd gekalibreerd met empirische gegevens.

Het empirisch gefundeerde model maakt het mogelijk de relatieve bijdrage van de gesimuleerde processen te bepalen. De resultaten laten zien dat maximaal 46% van de totale impact van de technologie werd veroorzaakt door gedragsdiffusie. Dit resultaat bevestigt het eerder vastgestelde belang om gedragsdiffusie mee te nemen bij het beoordelen van feedbackapparaten.

Op basis van eerder ontwikkelde modellen, gefundeerd met empirische gegevens, zijn beleidseffecten bestudeerd. Maatregelen die, zoals uit de literatuur blijkt, de adoptie van apparaten succesvol ondersteunen, zijn opgenomen in de analyse. De set van bestudeerde beleidsinstrumenten zijn het verhogen van de bekendheid, het gratis verschaffen en het uitlenen van feedbackapparaten. Deze marketingstrategieën werden gesimuleerd met vergelijkbare sterkte (in termen van het aantal gebruikte apparaten) en schaal (in termen van de geografische schaal en tijdshorizon). De instrumenten zijn getoetst door het simuleren van diverse implementatiescenario's. Op basis daarvan zijn de instrumenten vergelijken qua effectiviteit en kostenefficiëntie.

De resultaten laten zien dat het uitlenen van de apparaten bijzonder effectief is, terwijl het vergroten van hun bekendheid het meest kostenefficiënt lijkt. In het algemeen hebben de beleidsinstrumenten veel effect of de impact van feedbackapparaten. Dit laat duidelijk de noodzaak zien om een gewenste diffusiestrategie te selecteren om de impact van feedbackapparaten te maximaliseren.

Ten slotte is de voor dit proefschrift ontwikkelde methode gestandaardiseerd en verenigd in een aanpak voor automatisering. Deze aanpak heeft geresulteerd in prototype automatische software. Dit maakt het mogelijk automatisch agentgebaseerde innovatie-diffusiemodellen te genereren en daarmee beleidsinstrumenten te evalueren. Kandidaten voor innovatie-diffusiemodellen werden gevarieerd in structuur en parameters om de aannemelijkheid van elk van die mogelijke modellen voor een casus te kunnen bepalen.

De potentie van beleidsinstrumenten om diffusie te bevorderen wordt geëvalueerd op basis van (mogelijk meerdere) aannemelijke modellen. Het standaardiseren van het modelleerproces versnelt datzelfde proces en maakt het mogelijk om empirische data meer systematisch in te zetten. Daarnaast stelt deze aanpak ons in staat om bestaande modellen te verbeteren en leidt het tot het ontwikkelen van modellen die valide zijn door hun ontwerp. Samen laat dit zien dat de aanpak voor automatisering een succesvolle bijdrage levert aan de methode waarmee innovatie-diffusie wordt gemodelleerd.

Het kan worden geconcludeerd dat de impact van feedbackapparaten succesvol kan worden vastgesteld door de co-diffusie van de apparaten en de gedragsverandering die ze veroorzaken systematisch te simuleren. Deze conclusie is gebaseerd op vier pijlers.

Ten eerste is dat de bepaling van de impact, welke is gebaseerd op de ontwikkeling en simulering van het raamwerk van co-diffusie van technologie en gedrag. Dit heeft geleid tot een algemeen begrip van de mogelijke impact van feedbackapparaten. Ten tweede is dat de theoretische analyse die werd verfijnd met empirische data. Ten derde is dat het empirische model dat is ontwikkeld voor het bepalen van het potentieel van beleidsinstrumenten in termen van het beïnvloeden van het effect van feedbackapparaten. Ten vierde is dat de automatisering die de analyse van deze impact krachtiger en meer toegankelijk maakt. Uiteindelijk verbetert deze systematiseringsslag de manier waarop agentgebaseerde innovatie-diffusiemodellen worden ontwikkeld en toegepast.

1

INTRODUCTION

Motivation is what gets you started;
Habit is what keeps you going.

Jim Ryun

1.1. MOTIVATION

To tackle climate change and to deal with the depletion of fossil resources, a decrease in greenhouse gas emissions is urgently needed (Edenhofer et al., 2014). Residential heating represents a significant share of overall greenhouse gas emissions in the EU. *"Buildings represent 40% of the (European) Union's final energy consumption"* (European Parliament, Council of the European Union, 2012). For residential buildings, ca. 57% of this final energy is used for space heating (Itard and Meijer, 2008), the majority of which is generated from non-renewable energy (Olivier et al., 2015). The resulting contribution to overall greenhouse gas emissions in the EU is significant and therefore needs to be addressed as urgently as overall emissions.

A particularly cost-effective way to mitigate these emissions from space heating is via energy efficiency (Birol, 2008). Additionally, the EU committed to 20% increased energy efficiency in 2020, compared to the energy consumption that was projected in 2007 (European Parliament, Council of the European Union, 2012). However, final energy consumption of households in the EU failed to reduce significantly over the last 20 years (Eurostat, 2016). The building stock thus continues to bear significant potential to meet this energy-efficiency target. Everything else being equal, this potential should be addressed as soon as possible, because earlier mitigation allows for lower average atmospheric temperatures (IPCC, 2007). Therefore, mitigation solutions are needed that are not only effective, but also quick. With residential building envelopes in Europe having an average service life of ca. 60 years (Balaras et al., 2005b, Table 2), the largest near-term potential for reduction in energy demand of the building stock lies in existing buildings (Balaras et al., 2007).

Consumer behavior When increasing energy efficiency of existing buildings, potential from behavior change can have a valuable contribution, First and foremost, behavior change has the advantage to be of significant magnitude. Only due to different behavior, heating energy consumed in similar buildings can vary threefold (Gill et al., 2011). On average, significant savings of ca. 20% can be achieved from conservation behavior (Lopes et al., 2012). Additionally, behavior change has strategic benefits regarding implementation. Interventions to change energy-consumption behavior can be quickly implemented, are of low cost and scalable (i.e. widely applicable in the built environment) (Loock et al., 2013). Further, they require fewer physical resources than other energy-efficiency measures, e.g. renovation of buildings (Balaras et al., 2005a). Given the combination of these benefits, saving energy via behavior change appears to be the low hanging fruits to energy-efficiency in buildings.

Feedback interventions To achieve behavior change in domestic heating, users of buildings should receive feedback on their energy consumption. According to a recent meta-study by Karlin et al. (2015), feedback interventions to user behavior showed to reduce energy consumption by an average of ca. 7%. Long-term interventions (of at least 12 months) even achieved average savings of ca. 15%. Behavioral feedback was more successful if provided immediately, over longer periods of time, and via a digital medium. Therefore, electronic *feedback devices* that can be permanently placed in the household (e.g. in-home monitors or smartphone applications) appear best suited. Such devices rely on retrieving behavioral data from sensors or other 'Smart Home' appliances. Improvements of sensing technology and digitization of energy infrastructure are currently expanding the options for behavioral *"information to be collected, processed, and sent back (as feedback) to consumers quickly, cheaply, and often in real time"* (Karlin et al., 2015). Beyond its present capabilities, this technological potential can be expected to grow significantly with the future improvement of sensors and the market penetration of the 'Smart Home' and 'Internet of Things'.

Feedback devices The feedback devices that this thesis focuses on are designed to persuade their users to practice energy conservation. For persuasion, they use so-called 'nudging' (Thaler and Sunstein, 2009), which suggests users to change their behavior without forcing them to do so.

Changing behavior via feedback is challenging, because it has to 'break' existing habits, which are difficult to change (Jackson, 2005). Energy consumption behavior at home is particularly routinized: we may stand up in the morning, turn on the thermostat, and we go to sleep after turning it off again. Such habits circumvent thorough cognitive processing, at which conscious intentions influence actions and could make a difference (Jager, 2003). Therefore, interventions that only provide information to address intentions of energy consumers might fail. Instead, interventions should interrupt habits during their execution (Gärling and Axhausen, 2003) and instantly *nudge* users to practice another behavior. Over time, this approach has shown to be successful at replacing a habit with a new one (Piacentini et al., 2010). For a detailed presentation of the interaction of feedback devices with their users, see Chapter 2.2.

In the following, two examples of feedback devices are presented. Both of these incentivize conservation behavior. First, so-called 'Transformational Products' are devices that become a *material part* of the routines they are designed to change. They are described in detail by Laschke et al. (2011) and Jensen and Chappin (2014). When an undesired habit is executed, the feedback can create 'friction' to interrupt habitual behavior Laschke et al. (2011). At this window of conscious awareness, users are then able to consciously align action with their goals and values. Ideally, a Transformational Product now adds persuasion to 'nudge' users towards another habit (Thaler and Sunstein, 2009). An example of a Transformational Product is the so-called 'never hungry caterpillar', which is *"a caterpillar-like device that is supposed to be placed next to a TV. If the TV is switched to stand-by, it twists and thus symbolizes discomfort, which creates awareness (of) the waste of energy. Thus, awareness is created just in time and can immediately be translated into action"* (Jensen and Chappin, 2014). Second, the feedback device 'CO_2 meter' is designed to create healthier room ventilation behavior, but also showed to lead to energy savings. The device gives feedback on air-quality by presenting the measured indoor CO_2 levels in the intuitive colors of a traffic light. This information motivates households to ventilate rooms at higher air-exchange rates, but to stop ventilating when air-quality levels are sufficiently good. Indirectly, these two changes in behavior conserve heating energy (see Chapter 3). At field tests, this showed to create energy savings of ca. 8%.

Diffusion of feedback devices The impact of feedback devices (i.e. their overall effect on energy-conservation behavior) can consistently be framed as an innovation diffusion. The Theory of Diffusion of Innovations by Rogers (2003) describes an innovation as any idea that is *"new to an individual."* To this, Watts and Gilbert (2014) add that the innovation needs to be an improvement and of value to this individual. The diffusion of an innovation is *"the process by which an innovation is communicated through certain channels over time among the members of a social system"* (Rogers, 2003). Successful innovation diffusion can thus be seen equivalent to an innovation having great reach. This is what makes understanding the diffusion of innovations powerful. For this reason, Delre et al. (2010) stress the practical relevance of understanding the innovation diffusion of any new product.

In the following, the framing of feedback devices as diffusing innovations will be introduced in detail. The same will be done for the energy conservation that these devices incentivize. Previous to this thesis, these two diffusions had been researched individually, but apparently not in their interaction (Jensen and Chappin, 2014). Filling this research gap, this thesis integrates these two diffusions of *technology* and *behavior*, which are linked by the *feedback effect* of devices on behavior. Due to their linkage, these two diffusions are researched within a single framework. I coin this the *co-diffusion of technology and behavior* framework.

Technology diffusion will in this thesis describe the process of feedback devices spreading among consumers. When consumers decide on whether to adopt an innovation, they are *"motivated to reduce uncertainty about the advantages and disadvantages of the innovation"* (Rogers, 2003). This motivation results in exchange of information among consumers—e.g. via the mechanisms of word-of-mouth, which

1

can self-reinforce diffusion and can lead to a *take-off* of adoption (Rogers, 2003). Word-of-mouth has previously helped explain the successful take-off of the diffusion of many products (Delre et al., 2010, 2007). The importance of this mechanism is underlined by the Theory of Planned Behavior (Ajzen, 1991), which attributes human decisions (among other factors) to *subjective (social) norms*. Understanding the *technology diffusion* of feedback devices is able to draw on this theoretical foundation. Eventually, a take-off of diffusion to wide adoption would be helpful for feedback devices to have significant impact: the more adopters there are, the more persons will be exposed to behavior-changing feedback.

Behavior diffusion is the spreading of energy-efficient heating behavior among consumers. This concept bases on the Social Learning Theory (Ajzen, 1991). Accordingly, observation of other persons' behavior is an important source of an individual's learning. In an extensive review, Jackson (2005) concludes that this mechanism bears significant potential for sustainable behavior to spread. Likewise, numerous studies have concluded that diffusions of sustainable behaviors can be explained by social learning (Azar and Menassa, 2015; Mohammadi et al., 2014; Peschiera et al., 2010; Burchell et al., 2014). To describe this mechanism in the context of energy conservation, Azar and Menassa (2014) coined the process of *'diffusion of energy efficient behavior.'*

In the context of this thesis, behavior diffusion has the potential to reinforce the overall effect of feedback devices. For instance, assume that an intervention addresses consumer A, who then starts using a feedback device and adopts energy-efficient heating behavior. Now, consumer B, a close peer of A, might observe and imitate this new behavior and thus would also save heating energy. Consequently, such *behavior diffusion* could increase the overall impact of feedback devices beyond the impact for those households who are directly using feedback devices.

Effect of feedback from devices on heating behavior naturally links these two diffusions. Feedback devices have the potential to change energy consumption behavior of at least some of their users. If the diffusion of feedback devices takes-off, this could trigger adoption of conservation behavior on a large scale. This in turn would support behavior diffusion by exposing more parts of society to social learning of conservation behavior. In the physics community, this coupling of diffusions is actively researched as the 'diffusion in multiplex networks' (Granell et al., 2013; Funk and Jansen, 2010; Cozzo et al., 2013; Bagnoli et al., 2007). In essence, this field of research has shown that the interaction between two linked diffusions creates unique dynamics that can not be directly explained by any of its constituting individual diffusions. Consequently, exploring the *co-diffusion of technology and behavior* appears fruitful.

Simulating innovation diffusion Simulation modeling is promising at inferring the future impact of feedback devices. The benefit of simulating *"real-world systems is to give us something useful that we could not—for a variety of reasons—obtain from the system itself"* (Ahrweiler and Gilbert, 2005). Watts and Gilbert (2014) emphasize that simulation is useful to answer 'what-if' questions and to test policy actions. To understand ex-ante the future potential of feedback devices, simulating 'what-if' scenarios and policies is highly useful. At the time of writing, many feedback devices are still in the design

phase or their market diffusion has recently started. This is why forecasting their potential future impact is of particular interest. Thereby, it is important to remember that predicting socio-technical systems faces high uncertainty (van Dam et al., 2012). Fortunately, ex-ante insights do not strictly require precise prediction. Instead, Epstein (2008) stresses that *"bound(ing) (...) outcomes to plausible ranges"* can also be valuable. A confirmation of this forecasting capability of simulation is the model by Bass (1969). It has shown to successfully capture the macro-level dynamics of innovation diffusion.

A particularly suited approach for simulating the co-diffusion of technology and behavior is *agent-based modeling*. In practice, this is shown by numerous examples of successful simulation of innovation diffusions (see Watts and Gilbert, 2014; Kiesling et al., 2009)[1]. This success relies on three factors: its actor-based perspective, its capability to infer emergent system behavior from this micro-level perspective, and the disaggregated modeling of actor decisions (Chappin and Dijkema, 2015). First, households are the key actors of the research perspective that this thesis assumes. Agent-based modeling allows capturing their heterogeneity and socio-spatial structure, which are important factors for energy and sustainability related decisions of households (Grossmann et al., 2014). Second, simulating decisions and interactions of these micro-level agents generates an emergent system behavior on the macro level. This helps explain the dynamic inter-dependency of observations on both the micro- and macro-level of a system, which assists at making sense of both. Third, agent-based models capture in a disaggregated way the decisions of actors. Adoption decisions of technology and heating practices can successfully be captured, e.g. by using the Theory of Planned Behavior (Sopha et al., 2013; Schwarz and Ernst, 2009). This disaggregation has the advantage of giving valuable mechanistic insight instead of remaining a black-box that merely connects cause and effect.

However, disaggregation also makes agent-based modeling cumbersome, which calls for rethinking current modeling practice. Developing disaggregated models is relatively costly in time and labor (see Chapter 5). This has created two problems. First, this constraint often leads to 'ad hoc' decisions on model design (Grimm et al., 2005). In combination with many model design options, this has further led to a great variety of agent-based models of innovation diffusion (see Kiesling et al., 2012). Unfortunately, such high diversity is *"a major obstacle to distilling general insights"* (Thiele and Grimm, 2015). Second, high effort of model development has further contributed to the deficit that *"a versatile method of easily testing managerial strategies that influence the degree and speed of diffusion processes is not currently available"* (Garcia and Jager, 2011). Consequently, a systematic modeling approach that increases efficiency in developing agent-based innovation diffusion models and thus overcomes these downsides has yet to be designed.

Overall, the perspective of innovation diffusion and agent-based modeling are the right vehicles to increase understanding on the potential of feedback devices to reduce heating demand. First, diffusion view from the Theory of Diffusion of Innovations and Social Learning Theory, as well as theories of decision making like the Theory of Planned Behavior, are rich sources from which theoretical knowledge can be drawn. Second, agent-based modeling and simulation is suited as a methodological paradigm. This

[1] For a review of agent-based models of the diffusion of technology or behavior, see Chapter 2.4.2.

combination of theory and methods is useful to systematically simulate the potential impact of behavior-changing feedback devices. Such an approach could also be empirically grounded in order to complement the common approach of empirical field testing of devices. A model based on the empirical data from such field tests could further assist policy decisions on how to effectively support the impact of feedback devices. Ideally, all this should be taken out in a systematic modeling procedure that overcomes the current challenge of agent-based modeling of innovation diffusion being costly in time and labor.

1.2. RESEARCH QUESTIONS

The aim of this thesis is to give model-based insights into the potential of feedback devices to impact heating energy demand. This will be done from a perspective of innovation diffusion. Therefore, the central research question addressed by this thesis is as follows:

How can the impact of behavior-changing feedback devices on energy-consumption behavior be systematically simulated?

In the following are four sub-questions to this central question:

1. What are the mechanisms via which feedback devices can change heating behavior?
2. What is the impact of the diffusion of feedback devices and of the diffusion of the behavior that they incentivize?
3. How can the projected impact of feedback devices be affected by policies?
4. How can innovation diffusion models be developed and applied more systematically?

1.3. RESEARCH APPROACH

The stated research questions express the need to conduct a model-based study. The overarching method chosen is agent-based modeling of innovation diffusion. In the following, the research approach taken out in this thesis is presented in detail.

Simulating the impact of feedback devices is a valuable alternative to prevailing empirical research. So far, studies of empirical observation represent the bulk of research on feedback devices. We aim to complement this body of knowledge with a model-based study. Empirical observations have already created rich yet fragmented knowledge that modeling can take up and combine. Simulation modeling can be based on this existing empirical knowledge. The future of the simulated processes is of particular interest in this thesis. Therefore, simulation would be useful to explore possible future trajectories of impact from feedback devices.

The chosen research approach requires a stepwise proceeding. Its principal aim is to assess the impact of behavior-changing feedback devices by 'systematic simulation'.

Therefore, the research approach of this thesis works towards tackling this task via an automated software procedure. This approach promises a high degree of systemization and standardization. It builds on three preparatory steps. First, the mechanisms via which feedback devices create an impact are identified via simulation. Second, because the *real-world* impact of feedback devices is of interest, simulation are empirical-based. Third, the sensitivity of the impact to policies is explored systematically via scenario analysis. Finally, this groundwork is combined into an automated software procedure that makes the modeling process systematic. In the following, the succession of this research approach is presented in detail.

1.3.1. MECHANISMS OF IMPACT FROM FEEDBACK DEVICES

The first step of this thesis is to understand the mechanisms via which feedback devices create an impact on heating energy demand. This is done by developing an agent-based model that implements the framework of *co-diffusion of technology and behavior*. As an abstract technology case is chosen a feedback device that incentivizes heating at lower temperatures. Hence, modeled behavior is the thermostat setting by users—a central element to heating behavior.

Model building for this task combined existing models, which is not only efficient, but also transfers their previous validation. Two diffusion models—one of technology diffusion, one of behavior diffusion—are reproduced and integrated.

Simulation experiments are then used to identify the mechanisms and driving factors of co-diffusion. This helps highlighting the data needed for increasing model realism in the following research steps.

1.3.2. EMPIRICALLY-GROUNDED SIMULATION OF IMPACT

The simulation model from the previous step has to be refined to tackle empirical-based questions. The second sub research question is therefore answered by a simulation model that draws on data from field tests of feedback devices.

Commonly, the effect of interventions to energy consumption of households is analyzed with households, who test feedback devices, as final units of assessment (Darby, 2006; Grinewitschus et al., 2013; Karlin et al., 2014). In so-called *'Living Labs'* (Liedtke et al., 2015), interventions are tested right in the location for which they were designed. To quantify the induced change of behavior and energy consumption, testing is commonly accompanied by sensors that log behavioral data.

Instead of only in selected households, the initial motivation of this thesis demands that conservation of heating energy arises at *larger geographical scales*. This would contribute significantly to the reduction of energy demand in heating. Simulation modeling can help closing this gap across scales. With agent-based modeling and adequate socio-spatial data, it is possible to extrapolate findings from households to larger areas (Ernst, 2014). In this thesis, upscaling is conducted up to the city scale. A suited link for this upscaling is commercial marketing data that maps individual households and their sociodemographic properties.

When scaling up energy conservation, there are not only more households and more opportunities to save energy. Also, due to interactions between households, more processes take place that have to be captured. As described above, the diffusion

of feedback devices and the diffusion of conservation behavior become relevant in a system of multiple households. Capturing this co-diffusion in an empirically-based way therefore is a means to gain understanding of the impact of feedback devices on larger spatial scales.

This step of the research approach makes use of data from Living Lab experiments. Chosen case technology was the CO_2 meter, because close connection to empirical researchers has given access to sensor logging data from corresponding field tests. The chosen case area is the city of Bottrop (Germany), because rich marketing and building data is available from project partners and stakeholders.

Developing and validating an empirical-based model requires empirical data. Two patterns from empirical data are available for this: a historical trend of adoption of conservation behavior and data on the importance of social contacts at creating behavior change. These data were used to indirectly parameterize the simulation model. In line with the concept of 'pattern-oriented modeling' (Grimm et al., 2005), this coherence of the model with empirical data also assures its validity.

1.3.3. ASSESSMENT OF POLICY INTERVENTIONS

The third step of the research approach deepens the knowledge on the potential impact of feedback devices. In the previous steps, the impact of devices has been assessed while neglecting policies influencing the impact of devices. Nevertheless, the empirical-based model from this previous step provides the foundation for doing so. The means to answer the third sub research question therefore is to simulate policy scenarios.

The practical questions of how to influence the diffusion of feedback devices with marketing is tackled. A literature review guides selection of strategies (see Chapter 4.3.1). These then test with the simulation model from the previous research step. Addressed by this advice are policy makers, stakeholders, and marketers. This research step thus informs about what actions most effectively maximize the impact of feedback devices and which ones are most cost-efficient at doing so. Further, it creates a blueprint for assessing the role of policies towards the impact of feedback devices.

1.3.4. AUTOMATING AGENT-BASED MODELING OF INNOVATION DIFFUSION

The final research step combines the work from the previous three steps. The initial step contributes the framework via which diffusion of feedback devices is modeled. The second one contributed a method of building an empirical-based diffusion model based on empirical data. The third step contributes the structured testing of policy interventions.

In the final step, a procedure for generating and applying agent-based innovation diffusion models is presented. This addresses the fourth sub research question. The procedure is implemented as a software prototype of automated model generation. Automating the process of agent-based modeling in this thesis further includes the automated assessment of policies. Testing these with predictive models usually is a highly repetitive and time-consuming task. Automation is introduced to make this only repetitive and work-intensive for the used computing infrastructure, but not for users themselves.

1.4. OUTLINE

The structure of this thesis is shown in Figure 1.1. Each of the four sub research questions and steps of the research approach is covered by one thesis chapter.

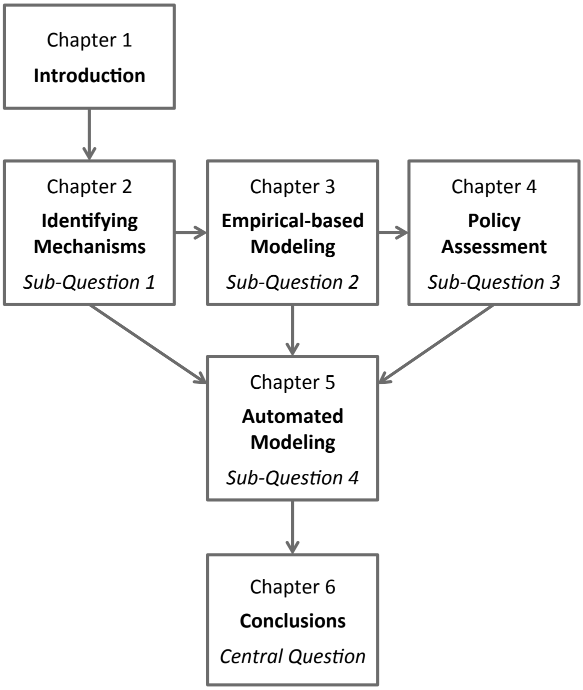

Figure 1.1: **Structure of this thesis.**

Chapters 2–4 successively expand modeling methods to generate knowledge on the co-diffusion of technology and behavior, as well as policy options. They take out the first three steps of the research approach. Based on this groundwork, Chapter 5 presents a method to automate the generation of agent-based innovation diffusion models and the assessment of policies. This chapter takes out the fourth step of the research approach. In the final thesis chapter, overall conclusions are drawn.

2

CO-DIFFUSION FRAMEWORK

First, earth had no roads
but as people walked on it
they thus made the roads

Lu Xun

2.1. INTRODUCTION

Reducing heating energy households consume is needed to mitigate climate change and the depletion of energy resources and, more specifically, to reach the EU target of a 20% gain in energy efficiency until 2020 (McDonnell, 2010). This is particularly important, because approximately 30% of energy in the EU is used in residential buildings and the bulk of this (ca. 57%) is used for heating (Itard and Meijer, 2008).

Changing the energy consumption behavior in households, e.g. setting lower space heating temperatures and heating fewer rooms, can significantly reduce heating demand at low investment costs and with few physical resources (Guerra-Santin and Itard, 2010). This is illustrated by the fact that different heating behavior in similar buildings can induce a three-fold difference between maximum and minimum energy consumption (Gill et al., 2011).

In this study, we focus on technical devices that provide feedback to households on their heating behavior and offer promise for supporting them to reduce their heating demand, i.e. to practice energy conservation. It has been shown that such devices can lead to typical energy savings of 10%, varying between an increase in energy consumption and savings of up to 30% (Darby, 2006; Karlin et al., 2014). Their success is based on the high frequency and the long duration of their feedback. First, frequent (e.g. daily) feedback supports habituation of changed behavior (Jager, 2003). Second,

This chapter has been published as Jensen, T., Holtz, G. and Chappin, E.J.L., 2015. Agent-based assessment framework for behavior-changing feedback devices: spreading of devices and heating behavior. Technological Forecasting and Social Change **98**.

providing feedback over a relatively long time-span prevents behavioral relapse and preserves the adopted energy conservation behavior (see Peschiera et al., 2010; Han et al., 2013; Burchell et al., 2014).

Ex-ante assessment of novel behavior-changing feedback devices is needed because different types of feedback vary significantly in their acceptance (Han et al., 2013) and how they reduce energy consumption (Karlin et al., 2014). Ex-ante assessments can reduce this uncertainty by eliminating the need to wait for data generated from actual market trials on a technology's effect. Failed market trials rooted in promoting and launching the 'wrong' types of products waste resources and time that could otherwise be directed to reducing energy consumption in households. Instead, distinguishing between more and less promising devices upfront helps support the diffusion of those devices that promise the greatest impact on energy conservation.

Existing methods for ex-ante assessment, e.g. trial testing (see Burchell et al., 2014; Grønhøj and Thøgersen, 2011; Darby, 2006), are useful for describing direct within-household effects of feedback devices. This approach estimates the direct impact of a device by comparing behavioral changes between a treatment and control group (Padonou et al., 2013).

However, we hypothesize that assessing only effects within households that use feedback devices underestimates the overall impact of feedback technology on energy consumption in a society. Instead, we argue that effects between households play an important role, as was shown for technology diffusion in assessments of environmental-friendly household technology (Schwarz and Ernst, 2009; Sopha et al., 2013; Afman et al., 2010; Delre et al., 2010). Additionally, we propose that diffusion of (changed) behavior needs to be included in assessments of behavior-changing feedback devices, too.

We argue that, in addition to within-household effects, assessing the overall impact of behavior-changing feedback devices on energy consumption needs to consider both the diffusion of behavior-changing feedback devices and the spread of behavior. The latter processes are both driven by the interactions between households. Direct communication, the so called 'word of mouth' interaction, strongly influences the number of households that adopt a new technology (Rogers, 2003), often reinforcing the extent new products are adopted and spread (Janssen and Jager, 2002; Schwarz, 2007; Rogers, 2003). Additionally, household interactions can spread the behavior induced by feedback devices beyond households adopting the devices (Nolan et al., 2008; Göckeritz et al., 2010). In particular, communicating energy consumption behavior between households is common (Baedeker, 2014) and comparing individual to peer behavior can trigger shifts in energy consumption behavior (Peschiera et al., 2010; Chen et al., 2012; Azar and Menassa, 2014).

In this study, we combine the aforementioned concepts to create a single technology assessment framework that covers (1) the direct impact that a feedback device unfolds within a household, (2) diffusion of the feedback devices among households, and (3) diffusion of (changed) energy consumption behavior. We furthermore implement an agent-based model based on this framework. We use simulation experiments to explore the relevance of the added behavior diffusion and to identify the relevant mechanisms.

The remainder of this chapter is structured as follows. First, we describe the functions of behavior-changing feedback technology (section 2.2). Second, we describe the framework capturing the three relevant processes mentioned above (section 2.3). Third, two existing agent-based models are combined into a model that implements the presented framework (section 2.4). Finally, we use simulations from the combined model to identify and demonstrate the relevant interactions between the spreading of both feedback devices and energy consumption behavior.

2.2. BEHAVIOR-CHANGING FEEDBACK TECHNOLOGY

Fig. 2.1 shows how feedback devices can influence heating behavior. The context in which these devices interact has two components: (1) the feedback loop between a user and a heating system, and (2) human decision making on heating behavior.

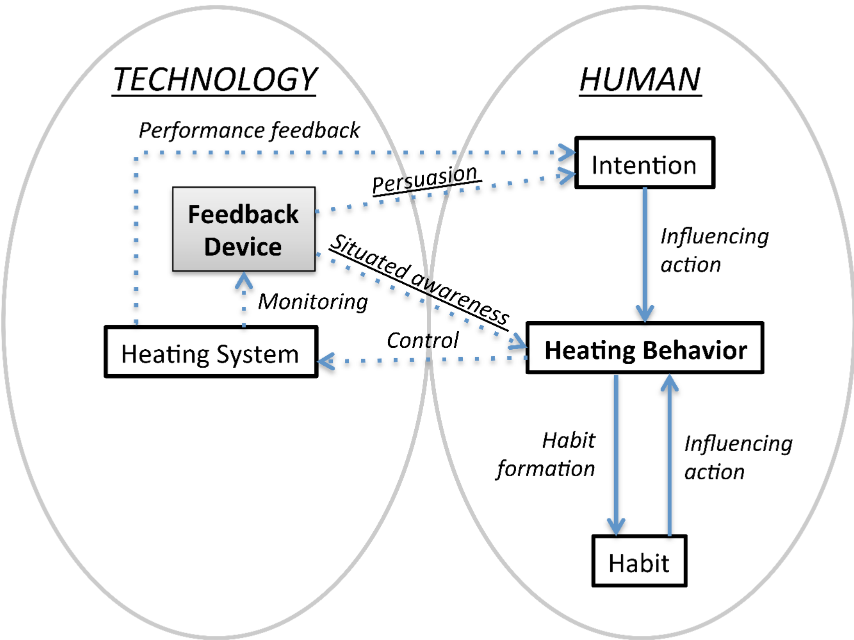

Figure 2.1: **Operation of behavior-changing feedback devices through interaction with the user.** The varied dashing of the arrows distinguishes the feedback between a heating system and its users (dotted lines) from the users' decision making (continuous lines). Underlined are the two presented means of feedback: persuasion and situated awareness.

Feedback loop Even without feedback devices, heating systems provide feedback on their performance to the users, who can then alter their behavior. For example, a user controls the temperature, which, if it is too warm or cold, incentivizes the user to change her heating behavior. Feedback devices can alter and enrich this feedback, e.g. by

associating higher energy costs with high temperatures, thereby motivating the user to change her heating behavior (Wood and Newborough, 2003).

The most common mechanism of feedback devices is using information to *persuade* users to change their behavioral intentions, i.e. *"the motivation required to perform a particular behavior, reflecting an individual's decision to follow a course of action"* (Armitage and Christian, 2003, p. 190). Feedback devices that rely on *persuasion by information* to address the user on a conscious level, e.g. by monitoring the user's behavior, visualizing it to the user, and thus creating awareness (Laschke et al., 2011), make energy consumption transparent and understandable (Wood and Newborough, 2003) and advocate a change in behavior. Smart Meters are a prime example for this (see Wood and Newborough, 2003). Another example is feedback devices that make energy consumption levels mutually transparent between friends so that behavior is influenced by peer pressure (Peschiera et al., 2010). Related to heating, an example is the E-quarium, which uses sensors distributed in the household to evaluate the users' energy consumption behavior (see Delft University of Technology, 2014). By scoring behavior, it involves the user in an incentive game that encourages use of lower heating temperatures. The scores are continuously shown by the 'happiness' of a virtual fish.

Feedback can also be given immediately at specific instances of behavior to create *situated awareness*. This can lead to users correcting performance. For example, Laschke et al. (2011) present the 'never hungry caterpillar', a so-called Transformational Product that is a caterpillar-like device placed next to a TV. If the TV is switched to stand-by, the device twists, symbolizing discomfort. This creates situated awareness of wasted energy and reminds the user that the TV can be switched off completely. Another Transformational Product could be a household item located close to a window that starts *shivering* if the window is open for too long during winter, emulating being cold and remind the user to conserve heating energy by closing windows.

Decision making Heating behavior follows intentions, but it is constrained by habits. *Habits* are action sequences that are performed without significant deliberation (Jager, 2003). They are triggered by so-called *environmental cues*. Repetition and positive outcomes of actions increase the strength of associated between cues and behavior (Jager, 2003). For example, saving energy costs by repeatedly turning down radiator thermostats, before leaving the home, supports habit formation. With frequent repetition in a stable environment, habits become reinforced, which makes them increasingly dominant over intentional behavior (Jager, 2003).

The feedback mechanism that uses *situated awareness* has the potential to change heating habits by interrupting them. This is because habits can effectively *"be changed through interventions that disrupt the environmental cues that trigger habit performance automatically"* (Verplanken and Wood, 2006, p. 90). Transformational Products, implementing situated awareness, thus seem particularly suited for changing heating habits.

2.3. CONCEPTUAL FRAMEWORK FOR TECHNOLOGY ASSESSMENT

In this section, we propose a framework for assessing the effect of behavior-changing feedback devices. In this framework, we combine the direct effect of heating feedback devices with first, the diffusion of this technology, second, the effect of feedback within a household, and third, the diffusion of the changed behavior. This framework is shown in Fig. 2.2 and defines the direction and interplay of these three processes from the perspective of one household as a model.

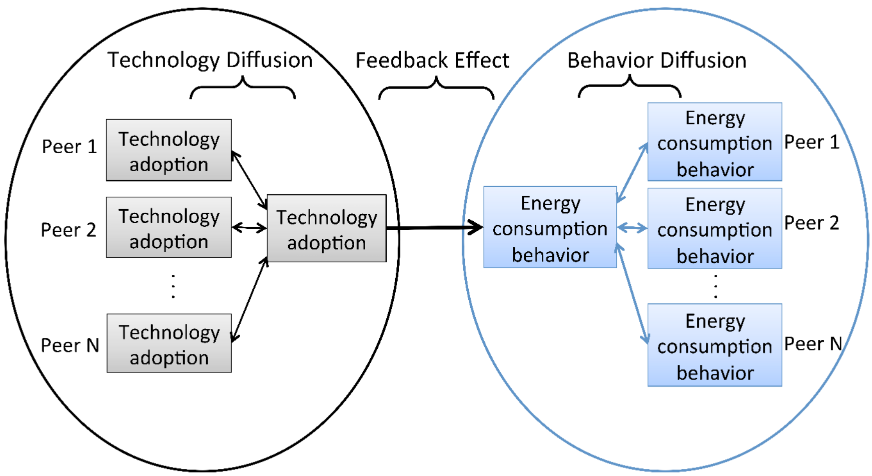

Figure 2.2: **Conceptual framework for assessing behavior-changing feedback technology.** A household's technology adoption decision (partially) depends on the adoption state of its N neighbors and in turn influences these peers' adoption decisions. Likewise, a household and its peers are mutually influencing their energy consumption behavior. If a household adopts feedback technology, then the feedback effect can also change its energy consumption behavior.

Technology diffusion is the process in which households adopt technology, i.e. choose to take up a specific feedback device. A well-known general characteristic of such processes is that the initial adoption by a few 'innovators' self-reinforces via word of mouth until a saturation level is reached (Rogers, 2003). As more people adopt a technology, the adoption choice persuades non-adopters to adopt. For example, empirical research shows that adopting water-saving shower heads by households can be positively influenced by the number of that household's peers who have already adopted such shower heads (Schwarz and Ernst, 2009).

The *feedback effect* is the direct effect of feedback devices on their users' heating behavior. It links the processes of technology diffusion and behavior diffusion.

We coin *behavior diffusion* as the spreading of energy consumption behavior (see Azar and Menassa, 2014), i.e. the phenomenon that *"behavior can be spread from one person to another via peer networks"* (Chen et al., 2012, p. 517). A key driver for behavior to spread is that of subjective norms, i.e. *"the perceived social pressure to perform or not to perform (a) behavior"* (Ajzen, 1991, p. 188). The social pressure is formed by

what a person perceives to be common and approved behavior. Subjective norms of conservation, which influence behavior of households, can explain why conservation levels between peers are highly correlated (Nolan et al., 2008; Göckeritz et al., 2010). Because people with strong social ties mutually influence their behavior (Bandura and McClelland, 1977), this influence is potentially transitive. This effect can thus spread further than one link in a social network. Consequently, heating habits are relatively similar within social groups (see Wilhite et al., 1996).

Behavior diffusion can act in any direction and may cause a so-called *boomerang effect*. This effect occurs when a person who uses less energy than her peers adopts a less stringent energy conserving strategy due to social influence (see Goldenberg et al., 2010). If this 'negative' social influence is strong, households could be resistant against the effects of behavior-changing feedback devices.

2.4. MODEL DEVELOPMENT

In this section, we develop a simulation model based on the presented framework. We first argue that agent-based modeling is a well-suited approach for this. We then present two existing agent-based models that each capture a substantial part of the framework, i.e. technology diffusion and behavior diffusion, respectively. Finally, we integrate these two models into a combined model.

2.4.1. AGENT-BASED MODELING

An agent-based model (ABM) captures real-world entities as autonomous computer agents, which *"have behaviors, often described by simple rules, and interactions with other agents, which in turn influence their behaviors"* (Macal and North, 2010, p. 151).

Agent-based modeling is a suitable tool for the given application for three reasons. First, ABMs are able to capture socio-technical systems that 'generate' emergent phenomena in a bottom-up manner (van Dam et al., 2012; Chappin, 2011; Epstein, 1996). Simulation results are thereby directly based on the micro-level units of assessment—in this case the household agents—and their behavioral rules and interactions. For example, the spreading of feedback technology and specific energy-consumption behaviors emerges from household interactions that can be modeled explicitly by an ABM.

Second, agent-based models are highly flexible in design because specifying rules is only limited by the programming language. This flexibility allows ABM to assimilate virtually all kinds of existing models, be they analytical or rule based, thus allowing us to integrate different existing models.

Finally, ABM is advantageous over many other modeling approaches when model entities are adaptive, heterogeneous and interact locally (Railsback and Grimm, 2011), all of which meet our modeling criteria. Households adapt their energy consumption behavior and adopt feedback devices depending on their peers. They are naturally heterogeneous in their product adoption preferences (Schwarz and Ernst, 2009). Further, interaction between households is more likely at smaller spatial scales (Baedeker, 2014; Holzhauer et al., 2013).

2.4.2. EXISTING TECHNOLOGY AND BEHAVIOR DIFFUSION MODELS

Various ABMs have been developed for diffusion of sustainable household technology (Schwarz and Ernst, 2009; Sopha et al., 2013; Kroh et al., 2012; Zhang and Nuttall, 2011) and energy consumption behavior (Azar and Menassa, 2014; Chen et al., 2012; Anderson et al., 2014; Zhang et al., 2011). A previous review by Jensen and Chappin (2014) found none of these models capture the proposed framework by connecting the two diffusions of technology and behavior. However, the two models by Schwarz and Ernst (2009) and by Anderson et al. (2014) were identified as particularly useful to model one of these two diffusion processes, respectively. In the following, we present these models and their potential to contribute to the proposed framework.

Technology diffusion The model by Schwarz and Ernst (2009) simulates the diffusion of environmentally friendly technologies between households. Households are of specific sociological lifestyles, i.e. social groups that share values and attitudes (Bourdieu, 1984). The empirical-based distribution between these lifestyles is shown in Table 2.1.

Table 2.1: Share of overall population of lifestyles, based on commercial marketing data for an area in Bavaria, Germany, with ca. 10 million inhabitants (see Schwarz and Ernst, 2009).

Sociological Lifestyle	**Share (%)**
Postmaterialists	10.9
Social leaders	20.4
Mainstream	24.7
Traditionalists	26.3
Hedonistic	17.8

A key component of the model is an empirical-based decision model for adopting environmental-friendly household technology. Adoption decisions are modeled on an empirical survey inspired by the Theory of Planned Behavior (see Ajzen, 1991), which stipulates a decision depends on the weighted sum of (1) the *attitude* towards the product, (2) the *subjective norm*, i.e. the ratio of an agent's adopting peers and (3) the *perceived behavior control*, which is the subjective effort of implementation (see Schwarz and Ernst, 2009, Fig. 1 & 2). These three criteria are partly sensitive to the lifestyle (which weigh decision criteria differently) and the specific sustainable technologies analyzed (which have product properties regarding these criteria).

Schwarz modeled the adoption choice with 13 parameters, which are derived from surveyed stated preferences. In the resulting ABM, some lifestyles are modeled to rationally deliberate on technology adoption, whereas others use a decision heuristic of bounded rationality. Postmaterialists and Social Leaders compare and weigh many product characteristics to reach an adoption decision (Schwarz, 2007). Therefore, they are modeled to deliberate but not be influenced by the subjective norm. Conversely, Hedonists, Mainstream, and Traditionalist lifestyles consider fewer criteria when deciding on adoption of technology. They are modeled to apply the so-called *take-the-best heuristic*, i.e. they decide according to the most important stated decision criterion that clearly favors one choice option. If the most important criterion does not clearly favor one option decision, the next most important criterion is used. If no

clear decision can be reached, agents imitate the majority of their peers. Note that the subjective norm may be one decision criterion, and that the social environment hence may have an effect on these lifestyles.

For the scenario of diffusing water-saving shower heads for which Schwarz and Ernst have implemented the ABM, this detailed empirical decision model is mathematically equivalent to simpler decision rules: If deciding, each lifestyle—according to a specific probability—either adopts the technology or decides according to the majority of its peers. Lifestyles that deliberate are always deciding in favor of the environmental-friendly option. The Mainstream and Traditionalist lifestyles adopt water-saving shower heads with a probability of 0.5 and imitate the majority of their peers otherwise. Households of the Hedonistic lifestyle always imitate the majority of their peers. Because only three different decision rules exist for five lifestyles, we are grouping the lifestyles according to their decision-making rules.

Behavior diffusion The model by Anderson et al. (2014) captures how energy consumption behavior spreads in social networks and describes how households change the energy they consume by social influence. Thereby, the greater the difference in behavior between a household and its social environment, the greater is the household's motivation to change behavior towards its peers (Festinger, 1962).

Behavior diffusion is described by a general social influence model, see Eq. 2.1.

$$\beta_{i,t} = \beta_{i,t-1} + s_i \cdot \left(\frac{\sum_{j=1}^{N} w_{ij} \cdot \beta_{j,t-1}}{\sum_{j=1}^{N} w_{ij}} - \beta_{i,t-1} \right) \tag{2.1}$$

The energy consumption behavior ($\beta_{i,t}$) of an individual (i) at a certain time (t) depends first on her previous energy consumption ($\beta_{i,t-1}$) and second on how much the previous energy consumption of her $N-1$ peers ($\beta_{j,t-1}$) differs from the individual's own energy consumption, weighted by the strength of social ties (w_{ij}). Behavioral change according to the second factor is scaled by the individual's susceptibility to subjective norms (s_i).

This model captures empirical phenomena of behavior diffusion that other models do not (see Chen et al., 2012; Zhang and Nuttall, 2012; Azar and Menassa, 2014). First, in addition to spreading more stringent energy conservation, more stringent energy conservation can diffuse. The model thus captures the boomerang effect (see section 2.3). Second, individual susceptibility to behavior diffusion (s_i) provides one way to capture habits. According to the model, if an agent's behavior were habitual, s_i would be lower and behavior would thus change (significantly) slower. This model, however, does not capture the processes of habit formation and reinforcement.

2.4.3. Integrating two existing models into a combined model

Rather than developing a model from scratch, we emphasize the importance of integrating these two selected existing models into one combined model to implement the proposed framework. Continuing to develop existing models promotes

good scientific discourse because existing models strengthen the empirical and methodological basis of a new model directly and transparently (Windrum et al., 2007). It thus roots the model developed in this study directly in existing knowledge. It also furthers knowledge on the existing model. This transfer of model validity is also called *TAPAS validation*, which is abbreviated from *Take A Previous model and Add Something* (Frenken, 2004).

In the following, we present the integration of the two existing models in four steps: First, we discuss their theoretical alignment, given their theoretical differences. Second, model adaptions were made to them to make them compatible and to transfer them to the case of heating feedback devices. Third, we re-implemented them according to these adaptions. Finally, these two models were linked via the effect of adopted feedback devices on heating behavior and a social network based on empirical data.

Theoretical alignment Despite their strong similarities, the two combined models have theoretical differences. Both model how innovations diffuse and emphasize social network interactions as their driver. However, two differences remain.

First, the behavior diffusion sub-model emphasizes imitation between agents, whereas the technology diffusion sub-model assumes mixed deliberation and imitation. This disparity is justified by varying levels of uncertainty in both decisions (Festinger, 1954) and has been successfully applied in previous ABMs (e.g. Janssen and Jager, 1999). On the one hand, adoption of a household device involves a one-time decision, based upon the perceived device properties. For example, a feedback device needs to be purchased and installed only once and thereafter remains active. Because this is a one-time action, it involves a delimited process of *deliberation*, which is driven by intentions. Conversely, behavior change *"must be repeated or continual to achieve maximum energy-savings: they rarely cost money, but they do ask change in habit and lifestyle adjustment..."* (Han et al., 2013, p. 707). Repetitive actions, which lack a delimited deliberation process, are thus less rational and, importantly, are commonly highly uncertain in their energy related effects (see Costanza et al., 2012).

Second, due to different qualities of available empirical knowledge, the models differ in household heterogeneity. The model of Schwarz and Ernst differentiates between lifestyle groups, while the model of Anderson does not. However, we argue this difference in detail does not compromise the theoretical compatibility of the two models.

Model adaptions The technology diffusion model by Schwarz and Ernst (2009) had to be reinterpreted as a model of individual households, which involved changes to the social network. Originally, the model uses spatially aggregated household agents (i.e. each represents all households of one lifestyle within one square kilometer) which are connected in a small-world network. When diffusing novel technologies, the initial phase of diffusion is relevant, where only a few adopters exist. Therefore, a higher resolution is more appropriate for representing these few first adopters. We thus assume the agents represent individual households in a social network.

Because detailed adoption decision models for heating feedback devices are not available yet, we use water saving shower heads, which are better researched by Schwarz

2

and Ernst (2009), as a proxy technology. In this conceptual study, a proxy technology needs to meet the requirement of being *qualitatively* similar regarding its diffusion (e.g. the device should be preferred by the same lifestyle groups). We argue our model meets this requirement, because they generally serve the same function in households: they save energy related resources (i.e. hot water and space heating energy, respectively) in daily household routines. Further, both technologies are similar according to at least three of Rogers' (2003) innovation characteristics: *Compatibility* (i.e. which sociocultural values and beliefs are affected by the innovation) is similar, as the technologies both conserve thermal energy linked to daily consumption behavior and are both installed inside the household. *Complexity* (i.e. perceived difficulty of use) is low for both technologies. Water saving shower heads are quickly installed. Likewise, messages from feedback devices should be self-explanatory. *Trialability* (i.e. *"the degree to which an innovation may be experimented with on a limited basis"*, (Rogers, 2003, p. 16)) is also similar, because both devices are low-cost and easy to start and discontinue within the household.

The behavior diffusion model by Anderson et al. (2014) need not be adapted to be integrated into the combined model. The behavior state variable was altered to represent heating behavior, defining the modeled heating behavior as *average space heating temperature*. This function was chosen because heating temperature significant affects energy consumption in buildings (Guerra Santin et al., 2009).

Reimplementation The existing models were re-implemented in the NetLogo framework (Tisue and Wilensky, 2004). Previously, the model by Schwarz and Ernst (2009) had been implemented in Java. Because the initial model implementation was not completely available, re-implementation was based on a PhD thesis (see Schwarz, 2007). The model by Anderson et al. (2014) had been implemented in the *Repast J 3.0* framework (North et al., 2013). Being structurally simple, this model was re-implemented based on Eq. 2.1.

Linking existing models to implement the framework To implement the framework, we considered how feedback technology affected heating behavior for adopting households. Modeled by Eq. 2.2, we assume that feedback devices alter behavior towards an incentivized level (β^*_∞) and that this behavioral change proceeds asymptotically (with the rate of Δ_β).

$$\beta_t = \beta_{t-1} + (\beta^*_\infty - \beta_{t-1}) \cdot \Delta_\beta \tag{2.2}$$

The principle of an incentivized target behavior is demonstrated, for example, by the E-quarium, which offers its most positive heating feedback only if the room temperature is at the normative goal of 18°C. An asymptotic learning curve is appropriate because it simulates two important aspects regarding behavioral change. First, a steadily decreasing behavioral change effect of feedback technology. At later stages, user engagement in feedback can decrease, suggesting the early phase of feedback is the most important for behavioral change (see Peschiera et al., 2010). Second, the asymptotic learning curve suggests feedback has a higher potential to alter behavior if the normative goal of feedback is significantly different from the user behavior. This is

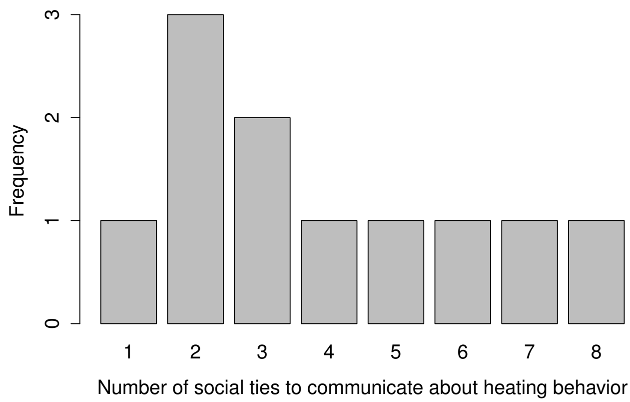

Figure 2.3: **Empirical degree distribution of social network.** Distribution of the number of relationships within a city through which a household communicates on heating behavior, based on interviews (Baedeker, 2014).

because saving energy by altering behavior has decreasing returns: the lower a person's energy consumption behavior is, the less options available to further reduce energy consumption. These remaining options are likely to be less practical and effective. For example, turning off the thermostat when leaving a room or the house is practical and effective, whereas turning down the thermostat when inside the room is likely less appealing to many people.

Finally, the agents are linked to each other via a social network, which models the communication regarding adoption of both technology and behavior. We based the network structure on interviewed ego-networks of communication on heating behavior between households (Baedeker, 2014), and on literature (Watts and Strogatz, 1998). The modeled social network matches two statistical properties of the empirical ego-networks: the degree distribution (i.e. with how many other households does an agent communicate, see Fig. 2.3) and the probability for such communication to be of short distance (p_{NBHD}) (i.e. within the same neighborhood of a city). In principle, all lifestyles can connect. But to account for homophily within lifestyles, there is an increased probability of connections within the same lifestyle (scaled by parameter h). The network creation is presented in detail in A.

We implemented the proposed framework using this integration. For its initialization, agents are created and linked in a social network. Then, at each time step, the sub-models technology diffusion, feedback effect and behavior diffusion are applied successively. For further model details, see A.

2.5. SIMULATION EXPERIMENTS

The purpose of this study is to propose, implement and explore an assessment framework for behavior-changing feedback devices. This framework complements trial

testing of such devices and simulating their diffusion by also simulating the diffusion of the behavioral change they create. In this section, we are using simulation experiments to investigate the relevance of combing these three processes into one framework.

We present three simulation experiments. In the first one we simulate only the diffusion of feedback devices, but not the diffusion of behavior, and reproduce the simulation results of Schwarz and Ernst. This verifies the way we re-implement the model and serves as a reference against the effects of adding processes in the following experiments. The second experiment extends this scenario to the proposed framework by adding the two processes of feedback effect on behavior and behavior diffusion. In this simulation we focus on the heterogeneity of the agents' heating behavior in order to identify the added effect of behavior diffusion in detail. In the third simulation we vary strength of the feedback effect and behavior diffusion to explore how heating feedback devices affect the behavior of different lifestyles. This aims to observe the effect of behavior diffusion on a larger scale.

The model proceeds at time steps of one month and the simulation runs terminate after 30 simulated years. The parameterization for the simulation experiments is given in Table 2.2.

Table 2.2: **Parameterization** for the simulation experiments. Where a source is given, the parameter value is empirical based. Else, the value is either chosen generically or varied extensively.

Paramter	Value	Meaning	Source
$\|N\|$	3000	Number of household agents	-
d_{NBHD}	10	Range for links within neighborhoods	-
p_{NBHD}	0.5	p(Link within neighborhood)	(Baedeker, 2014)
h	0.4	Homophily in social network	-
deg_i^*	[1,8]	Degree of agent i	(Baedeker, 2014)
t_0	1990	Initial time step	(Schwarz and Ernst, 2009)
t_{max}	2020	Final time step	(Schwarz and Ernst, 2009)
Δ_t	1	Months of time step length	(Schwarz and Ernst, 2009)
$\alpha_{i,t} \in \{0,1\}$	-	Technology adoption variable	-
δ_α	0.004	Tech. adoption decision probability	(Schwarz and Ernst, 2009)
$p(\alpha_{i,t=0})$	0	Init. technology adoption rate	(Schwarz, 2007)
$\beta_{i,t} \in \mathbb{R}$	-	Energy consumption behavior	-
$\beta_{i,t_0}, \forall i \in N$	21.1	Init. energy consumption behavior	(Shipworth et al., 2010)
β_∞^*	18	Behavior incentivized by feedback	-
Δ_β	[0,1]	Susceptibility to feedback	-
s_i	[0,1]	Susceptibility to behavior diffusion	-
w_{ij}	{0,1}	Link strength between agent i and j	(Baedeker, 2014)

2.5.1. REFERENCE SCENARIO OF TECHNOLOGY DIFFUSION

In the first simulation experiment we present the spread of environmental-friendly technology between households generated by the technology diffusion sub-model. This serves as a reference scenario to consider only the spread of heating feedback devices and not the diffusion of behavior. Fig. 2.4 compares simulation results to empirical market shares of a proxy technology.

The simulation results show that adopting environmental friendly household technology significantly differs between households. The lifestyles of Postmaterialists

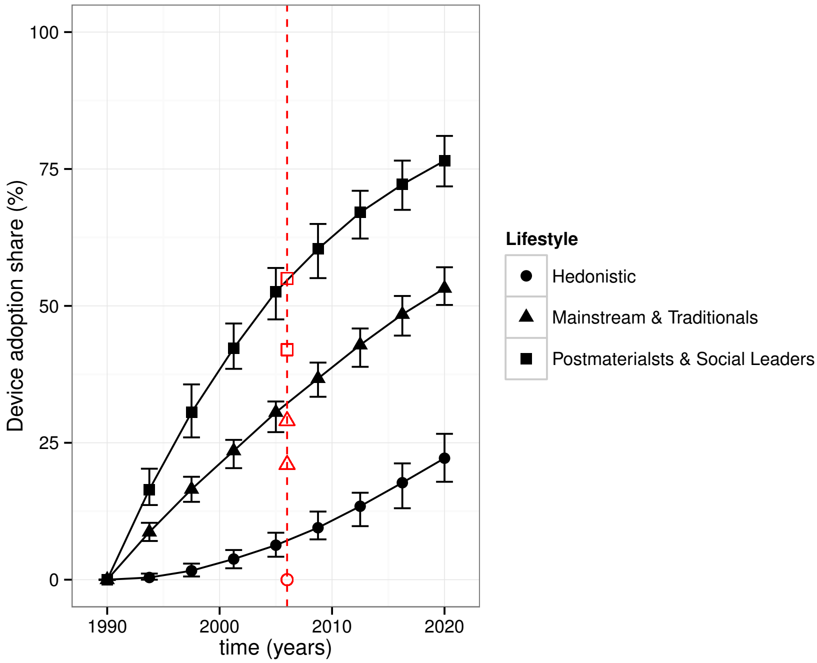

Figure 2.4: **Modeled adoption share of feedback devices over time.** Modeled market shares are based on the sub-model of technology diffusion that reproduces the model by Schwarz and Ernst (2009). The whiskers mark the 2.5th and 97.5th percentiles over the adoption shares from 60 simulation runs. Empirical market shares for the proxy technology of water-saving shower heads for December 2005 are shown by the hollow symbols on the dashed line, see Table 2.3 for details.

and Social Leaders are adopting this technology with the greatest rate. Conversely, the Hedonistic lifestyles barely adopt the technology. In between, the Mainstream and Traditional lifestyles show intermediate adoption.

These results successfully reproduce the previous results of Schwarz and Ernst (2009). First, the model generally matches the empirical market shares of the environmental-friendly proxy technology, see Fig. 2.4. Second, it matches these empirical data in the same range as the model as Schwarz & Ernst did, see Table 2.3. Our model deviates less than 20% greater than the empirical market share when comparing the model it is reproducing with the empirical market share. In addition, if we disregard the Hedonistic lifestyles, for which only three empirical adoption data points were given (see Table 2.3), the cumulative deviation is the same for both the original and the here reproduced model.

We can easily infer that, assuming no behavior diffusion and homogenous effect of feedback devices on households, the simulated difference in adoption between lifestyles would imply a proportionate difference in the effect of environmental-friendly technology between these lifestyles. The lifestyles that adopt such technology the most, i.e. Postmaterialists and Social Leaders, could thus profit the most from its effect. In

Table 2.3: Comparison of model reproduction with results of Schwarz and Ernst (2009) and empirical market shares.

Lifestyle	Model result [a]	Original model [b]	Market share [c]
Postmaterialists	51	53	55 (n=35)
Social leaders	51	53	42 (n=24)
Mainstream	32	18	29 (n=28)
Traditionalists	32	18	21 (n=21)
Hedonistic	5	0	0 (n=3)

[a] Mean adoption share (%) at simulation time December 2005.
[b] Adoption share (%) *post*dicted by Schwarz and Ernst (2009) at simulation time December 2005.
[c] Empirical market share (%) provided by Schwarz and Ernst (2009) for December 2005 (n ≡ sample size).

contrast, the Hedonistic lifestyles could not profit from the energy-saving effects of this technology.

2.5.2. ADDING FEEDBACK EFFECT AND BEHAVIOR DIFFUSION

In the second simulation experiment, we added to the above reference scenario the effect that feedback devices have on households' heating behavior as well as behavior diffusion. We assumed a fixed feedback effect strength which is identical for all lifestyles ($\Delta_\beta = 0.1$) and varied the level of behavior diffusion (s_i), the latter one being the innovative component we have added to previous studies and thus of specific interest to us.

In this scenario, we are interested in the change of agent heating behavior. We focus on heterogeneity of the agents' behavior because there are two contradictory processes at work: adopting feedback devices lead to behavioral change of (only) those households that have adopted and thus tend to increase heterogeneity of behavior; and behavior diffusion tends to smoothen the differences and make households more homogeneous. The interaction effects of these processes are not obvious but determine how behavior diffusion affects overall energy consumption.

The results of typical single simulation runs are shown in Fig. 2.5. For each level of behavior diffusion strength, a separate plot is shown. For each time step, we visualized the distribution of agents' heating behavior, i.e. their individual room heating temperature. Additionally, the aggregated average space heating temperature of all agents is plotted for each time step. We limited the observation to agents of the lifestyles of Social Leaders, the lifestyle group that most rapidly adopted feedback devices. This lifestyle group was thus expected to show a clear contrast in heating behavior between adopters and non-adopters.

The Figure shows that feedback devices have a different overall effect at different levels of behavior diffusion, regarding heterogeneity of agents' behavior and change of average behavior. For all behavior diffusion levels, the agents' heating behavior shifts from the initial temperature of 21.1°C towards 18.0°C, the temperature being incentivized by feedback devices. The distinction between the levels of behavior diffusion appears to be especially clear because the process of behavior change induced by the feedback devices operates on time-scales that are much shorter than the process of the diffusion of the devices. Yet, greater behavior diffusion causes (1), less

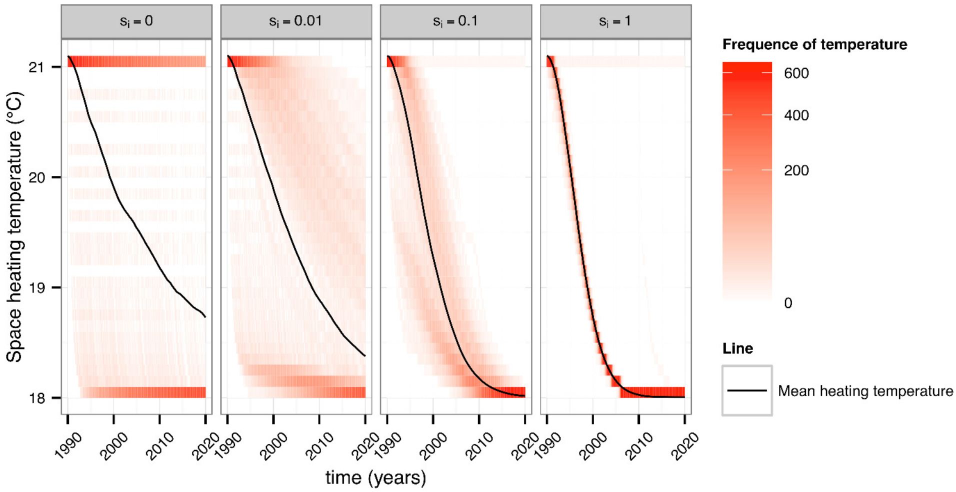

Figure 2.5: **Change in heating behavior of agents of the lifestyle Social Leaders when considering diffusing feedback devices, effect of these devices on households and behavior diffusion.** Strength of behavior diffusion (s_i) varies between plots. The color gauge shows vertically the distribution of space heating temperatures within one simulation run and its change over time shown horizontally. The line represents the mean of the agents' space heating temperature.

heterogeneity in agents' heating behavior and (2), faster rate and extent of average behavioral change. Note that both patterns are consistent between simulation runs. We discuss these two phenomena in the following section and analyze the underlying mechanisms.

Heterogeneity between adopters' and non-adopters' heating behavior Simulation results show that stronger behavior diffusion strength reduces the behavioral gap between adopters and non-adopters. At one extreme, without behavior diffusion, two space heating temperatures dominate, 21.1°C and 18°C: heating temperatures generally decrease from 21.1°C to 18°C. Thus, an increasing number of agents quickly change from the former to the latter heating behavior over time. This behavioral heterogeneity clearly distinguishes adopters from non-adopters of feedback devices. When behavior diffusion strength is greatest, heterogeneity between adopters and non-adopters is minimal and the transition for adopters and non-adopters from 21.1°C to 18°C is simultaneous. In between these two extremes, increasing behavior diffusion allows the heating behavior of adopters and non-adopters successively converge during the transition from 21.1°C to 18°C.

According to the applied model, peers imitate each other more when the strength of behavior diffusion (s_i) increases; at maximum, individual behavior is equal to the (weighted) average of peers' behavior, regardless of own previous behavior and the effect of feedback devices (see Eq. 2.2). Note that imitation is bidirectional and thus causes both adopters and non-adopters to approach the behavior of the other group.

Speed of change in average behavior At higher levels of behavior diffusion, the mean agent heating temperature decreases faster. Without behavior diffusion, a decreasing average heating behavior mirrors the increasing adoption of feedback devices. For instance, at the simulation year 2005, ca. 50% of Social Leaders adopt feedback devices (see 2.5.1). At the same time step, mean heating behavior has reached approximately half way from 21.1°C to 18°C. At increasing levels of behavior diffusion, the transition from 21.1°C to 18°C speeds up.

We argue that bidirectional imitation between agents alone fails to explain the increasing speed of change in average behavior. This is because even though adopters influence non-adopters towards lower heating temperatures, non-adopters similarly influence adopters to a similar extent. Behavior diffusion simply *distributes* the behavioral change from feedback devices between adopters and non-adopters. Because behavior diffusion is bidirectional, it can only result in a *zero-sum game*.

Instead, we argue that this phenomenon is caused by an interaction between the feedback effect and behavior diffusion. The feedback effect varies depending on the adopters' level of heating temperatures. As soon as adopters approach heating temperatures of 18°C, no further behavioral change occurs, which could be 'redistributed'. In contrast, at greater behavior diffusion, behavior heterogeneity between adopters and non-adopters decreases and adopters thus heat at higher temperatures. These higher heating temperatures increase the effect of feedback devices due to the modeled asymptotic feedback effect function. Additionally, behavior diffusion more efficiently distributes this effect.

In summary, stronger behavior diffusion leads to two phenomena. First, decreased heterogeneity of heating temperatures between adopters and non-adopters of feedback devices. Second, feedback devices motivate a faster transition to this behavior. The first phenomenon is influenced by agents imitating each other. The second by a combination of three factors: (1) greater behavior diffusion causes adopters and non-adopters to converge in their behavior, (2) which causes higher heating temperatures for adopters whose behavior is consequently more effected by feedback devices, and (3) at high levels of behavior diffusion, this greater effect can be efficiently distributed between adopters and non-adopters.

2.5.3. VARIATION IN FEEDBACK EFFECT AND BEHAVIOR DIFFUSION

With the following simulation experiment, we examine the effect of added behavior diffusion when different lifestyles are considered simultaneously: Which social groups are most affected by this effect? How does this effect differ between social groups?

As indicators we use the mean space heating temperatures of the households of each lifestyle. Detailed simulation settings are given in Table 2.2.

We both varied the strength of behavior diffusion (s_i) and the feedback effect on behavior (Δ_β), to systematically observe their added effect. This variation is motivated by uncertainty about de facto speeds of these sub-processes (see Anderson et al., 2014). We vary the parameters as follows to compare four scenarios:

- Scenario 1: Feedback does not change behavior ($\Delta_\beta = 0$),

- Scenario 2: Feedback changes behavior, but behavior diffusion is not present ($0 < \Delta_\beta < 1 \wedge s_i = 0$)
- Scenario 3: Feedback and behavior diffusion act at intermediate strengths ($0 < \Delta_\beta <= 1 \wedge 0 < s_i <= 1$)
- Scenario 4: Both feedback and behavior diffusion act at maximum strengths ($\Delta_\beta = 1 \wedge s_i = 1$)

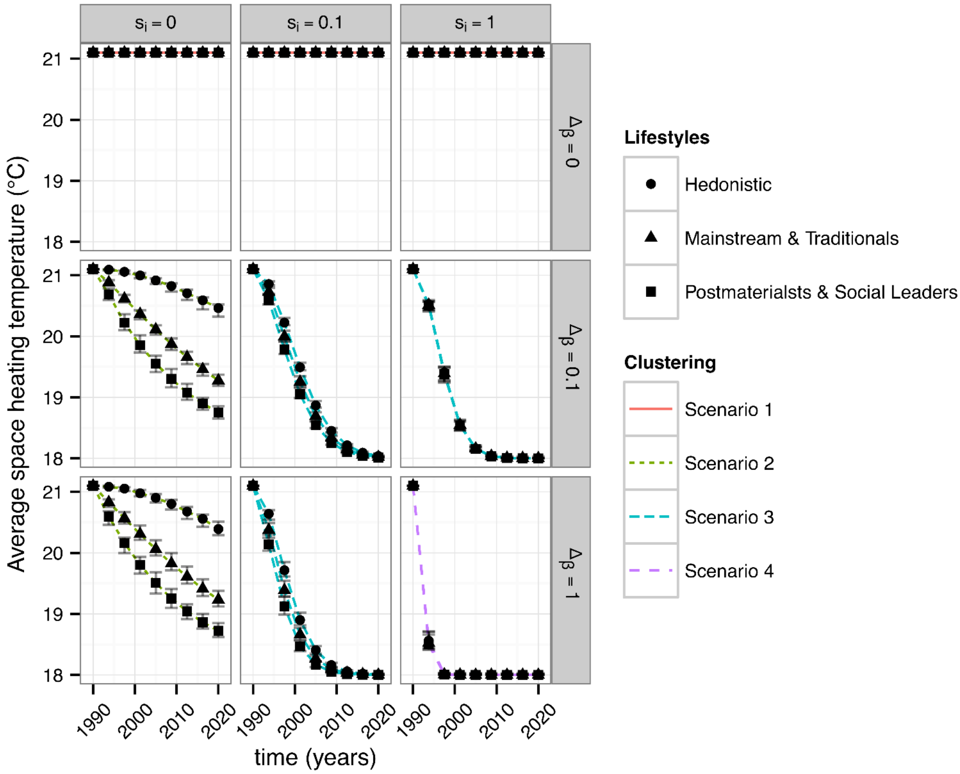

Figure 2.6: **Median of average space heating temperature of lifestyles over time.** Varying strength of feedback effect (Δ_β) and behavior diffusion (s_i). The multivariate timelines were clustered statistically to highlight model sensitivity. Line dashing represents the clustering result for each parameter combination (see legend). Whiskers show the empirical 2.5th and 97.5th percentiles of the lifestyles' average heating temperature of 25 simulation runs each.

The simulation results for these scenarios are shown in Fig. 2.6. Between the scenarios, mean heating behavior of the respective lifestyles differs significantly. This is confirmed by statistical clustering of the simulation results separating these scenarios.[1]

[1] Each simulation run resulted in one multivariate timeline of average space heating temperatures over time, distinguished by the different lifestyles. The pairwise distance between these multivariate timelines was

In scenario 1, in which technology does not change behavior ($\Delta_\beta = 0$), overall energy consumption behavior remains unchanged for all lifestyles. Thus, as can be expected, with no behavioral change, behavior diffusion simply has no added effect.

In scenario 2 (with feedback effect but without behavior diffusion), the pattern of behavioral change is similar to that when feedback devices are adopted. Feedback technology changes energy consumption behavior of adopters, but this behavior does not diffuse. Thus, behavioral change is directly determined by technology adoption (see Table 2.3). As with the first simulation experiment, Postmaterialists and Social Leaders were similarly affected first and to the highest degree. Mainstream and traditional lifestyles were affected shortly after. The Hedonistic lifestyle was affected last and to the lowest degree. The behavioral change over time was not sensitive to the strength of feedback effect on behavior (Δ_β). We assume this to be caused by households adopting technology relatively slowly compared to the time-scales on which the feedback effect operates.

In scenario 3 (with both feedback effect and behavior diffusion at intermediate levels), stronger behavior diffusion caused smaller differences in behavior between lifestyles, and absolute levels of energy consumption of all lifestyles decreased. At maximal behavior diffusion within this scenario, the differences in behavior seemingly disappeared, similar to those observed in section 5.2. For agents of the Hedonistic lifestyle, stronger behavior diffusion led to significantly lower room temperature compared to without behavior diffusion. A similar effect occured for the other lifestyles, but to a lesser extent. Thus, the less a lifestyle adopted technology the higher the added effects of behavior diffusion to its heating behavior. Of note, even the leading lifestyles (Postmaterialists and Social Leaders) reduce room temperature quicker if behavior diffusion is assumed, i.e. the additional 'redistribution' of changed behavior to other lifestyles does not (over-)compensate the effect discussed in section 5.2.

In scenario 4 (both feedback effect and behavior diffusion at maximum level), heating behavioral changed the quickest for all lifestyles, implying a synergistic effect of technology and behavior diffusion on energy consumption behavior.

2.6. DISCUSSION AND CONCLUSIONS

In this study, we have proposed, implemented and simulated an assessment framework for the overall effect of heating feedback devices on energy consumption. This framework includes the process of behavior diffusion for assessing heating feedback devices, which commonly considers their direct effect on adopters and, to a lesser extent, how devices diffuse between (potential) adopters.

This study confirms our initial proposition: the relevance of incorporating behavior diffusion into the assessment of such devices. Simulations revealed two mechanisms behind behavior diffusion driving the overall effect of heating feedback devices. First, behavior diffusion spreads the effect of feedback devices between adopters and non-adopters. It thus not only decreases heterogeneity of these two groups' behavior but also introduces a qualitative difference compared to technology diffusion by reaching

defined by their *Manhattan distance*. Hierarchical clustering into 4 groups was conducted applying *Ward's minimum variance method*.

non-adopters of devices. Second, simulations show behavior diffusion can considerably speed up the overall behavioral change caused by feedback devices. The convergence of energy-consumption behavior between adopters and non-adopters slows down adopters reaching the energy conservation level incentivized by feedback devices. This prolongs the effect of feedback devices on adopters, which is further propagated to non-adopting households through behavior diffusion.

In summary, we observe that behavior diffusion contributes significantly to the overall effect of feedback devices on energy consumption. Without behavior diffusion, lifestyles are only affected according to their share in adopting technology. Behavior diffusion reduces the differences in behavior between adopters and non-adopters and, when interacting with the feedback effect, synergistically increases the speed and degree of behavioral change for all lifestyle groups so the overall effect of feedback devices is stronger.

This finding supports previous research highlighting the potential for behavior diffusion to reinforce interventions for changing energy consumption behavior (see Peschiera et al., 2010; Chen et al., 2012; Anderson et al., 2014). In this chapter, we confirmed such an added effect of behavior diffusion with heating feedback devices exists, particularly when their simultaneous diffusion interacts.

2.6.1. IMPLICATIONS AND RECOMMENDATIONS

We focus on three aspects highlighting the implications of our study: (1) lessons on the difference between behavior-changing feedback devices and automation technology, (2) the fruitful interaction of two existing fields of diffusion research and (3) future applications of the proposed framework.

First, we stress feedback devices that support energy conservation can spread changed behavior beyond households adopting these devices, thus creating the positive externality of benefiting more households. We assume that this kind of externality is not specific to feedback devices, but to varying degrees inherent to any intervention that changes energy consumption behavior. In contrast, energy efficiency devices that do not change behavior, such as domestic energy efficiency automation technology, do not provide this externality. For example, heating automation devices, e.g. Google Nest, can potentially increase heating energy efficiency, but do not incentivize behavior change capable of spreading via behavior diffusion. These considerations underline the relevance of (also) analyzing behavior diffusion when assessing energy-efficiency devices.

Second, we highlight the added value of integrating technology diffusion and behavior diffusion models. In this study, integrating both types of diffusion models identified indirect effects from feedback devices that normally would not emerge with either diffusion model. We also assume interactions between these types of diffusions might be relevant in contexts where the effect of technology is behavior change.

Third, the synergy between diffusion of feedback devices and energy conservation encourages further research with this framework. This includes refining the simulation model to empirical scenarios.

2.6.2. LIMITATIONS AND FUTURE RESEARCH

Findings from the proposed technology assessment framework were based on a simulation model that integrates two existing models. The tight coupling between the conceptual framework and its implementation in this simulation model allowed us to analyze its concepts and integrate the framework more generally. However, as the main limitation of this study, the findings lack empirical support. Improving the model with empirical data thus constitutes a major route for future work.

We outline below methods for developing the presented framework into a more empirical-based model. Such a model would allow estimating more precisely the overall effect of feedback devices on heating energy consumption. Conversely, behavior-changing feedback devices could be compared ex-ante in how they conserve energy. Encompassing the mechanisms, speed and intensity of technology diffusion, feedback effect, and behavior diffusion for both applications should be based on empirical data. We present three practical steps for strengthening the empirical foundations required by both applications.

First, empirical data can make the model more realistic, e.g. by using pattern oriented modeling (see Grimm et al., 2005). Collecting data on how society influences energy consumption behavior is particularly challenging. Yet, research on how households interact regarding energy conservation levels identifies patterns useful for developing future model (see Baedeker, 2014; Nolan et al., 2008). In addition, field research in the realm on Living Labs and Smart Cities provides opportunities to gather empirical data on influence between households (e.g. respective to their belonging to lifestyle groups) (see Pentland, 2014).

Second, another route forward is making the decision-making more specific to heating behavior than in the existing models. One possibility is using empirically-based choice modeling (see Araghi et al., 2014). This allows considering other effects on heating behavior, e.g. fuel price.

Third, current field tests of novel feedback devices, e.g. Transformational Products, can better estimate the direct effect of feedback on behavior (see Liedtke et al., 2015). Focus groups of field testing participants can further knowledge on accepting over longer times periods, an important factor contributing to diffusion success (Rogers, 2003). This allows further investigation of the role habits play in the repeatedly observed relapse of behavior during long-term behavioral change interventions (see Peschiera et al., 2010; Chen et al., 2012).

Additionally, we can use the presented model to investigate heating feedback devices combined with energy-efficient retrofits of buildings, an important energy efficiency approach for the built environment (Guerra Santin et al., 2009). In this study, we model the overall effect of 'stand-alone' feedback devices on heating temperatures. Alternatively, one could model the application of feedback devices where both approaches, i.e. renovation and behavioral change, interact. Investigating how interaction of feedback devices and renovation interact is interesting as it has been found that retrofitting saves less energy (and heating costs) than expected due to the rebound effect (Friege and Chappin, 2014), i.e. users commonly increase heating temperatures after energy-efficient renovations and hence decrease the energy efficiency gain from the renovation. The assessment framework we developed could help investigating the effect

of feedback devices if they are available to households after energy-efficient renovations, e.g. through craft businesses.

2.6.3. CONCLUSION

Considering behavior diffusion when assessing behavior-changing feedback devices is important because it can significantly influence their overall effect. We identified two mechanisms through which behavior diffusion increases both the reach and speed of behavioral change induced by such devices.

We suggest that interventions that aim at changing behavior should exploit this synergy for increasing their effects. The proposed framework is useful for better capturing and eventually assessing the effect of such interventions on energy consumption behavior ex-ante.

3

Energy-efficiency impacts of an air-quality feedback device

"It's a dangerous business, Frodo, going out your door. You step onto the road, and if you don't keep your feet, there's no knowing where you might be swept off to."

J.R.R. Tolkien

3.1. Introduction

The main factors that determine energy demand of houses are (1) the climate, (2) building properties, e.g. heat permeability of building envelope, (3) efficiency of installed heating technology, and (4) the heating behavior of households, e.g. how to heat and how to ventilate rooms (Pérez-Lombard et al., 2008; Gill et al., 2011). In this paper, the focus lies on household behavior, which is an important pillar for reduction of energy consumption (Tukker et al., 2010). For instance, identical buildings can vary by a factor of over 3 between minimum and maximum energy consumption, only due to different users (Gill et al., 2011).

Interventions that persuade households to practice energy-efficient heating behavior are an attractive approach to reduce heating energy consumption with low overall effort. Two important advantages of focusing on household behavior are that (1) it is a low-cost option to mitigate CO_2 emissions (Birol, 2008), as no significant financial investment is required (Dahlstrom et al., 2012) and (2) behavior interventions are less prone (in comparison to building insulation) to trigger rebound effects in domestic heating (see Friege and Chappin, 2014). One example of efficient heating behavior is *'shock-ventilation'* (SV) (i.e. completely opening windows for 5 minutes two to four

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times per day), which saves up to ca. 25% of heating energy—with an average of ca. 8%—compared to commonly practiced trickle ventilation (i.e. ventilating at low flow of air, e.g. by opening windows only slightly)[1] (Grinewitschus et al., 2013; Lovric, 2015). Previous studies showed that these savings rely on both the quicker ventilation rate and on preventing the too long ventilation times of trickle-ventilation (Galvin, 2013).

Devices that provide feedback to households on their heating behavior appear promising as a means to change these routines. Their installation in households leads to a relatively high frequency of interaction with their users, supporting habituation of new behavior (Jager, 2003). One such device is the 'CO_2 meter', which visualizes indoor air-quality (measured by CO_2 level) in the colors of a traffic light. This feedback proved successful at persuading its users to practice SV behavior and to save heating energy (see 3.3.2). Such behavior change of device users is commonly identified by combined monitoring of behavior and energy consumption (Guerra Santin et al., 2009) (e.g. in 'Living Labs' in which interventions are tested in the users' real life surroundings (Liedtke et al., 2015)). The direct stimulation of behavior change within adopting households—in the following referred to as 'feedback effect'—, is the keystone of the impact of a feedback device.

However, the effect of the 'CO_2 meter' in a multi-household setting on a larger scale, such as a city, depends on additional processes (Jensen et al., 2015): (1) The technology diffusion of the feedback device among households, by which more households are exposed to feedback. Market research methods can give insights into future market diffusion of household devices. This ranges from qualitative field experimenting (Rogers, 2003, pp. 71) to quantitative simulation models that project future diffusion (Schwarz and Ernst, 2009; Sopha et al., 2013; Kiesling et al., 2012). (2) The diffusion of changed behavior via social influence that adopters exceed on non-adopters in their social environment. Social influence is a strong motivation for behavior change (Nolan et al., 2008; Liedtke et al., 2013) and thus has the potential to influence the overall effect of feedback devices (Jensen et al., 2015). The effect of feedback devices within households, the diffusion of devices, and diffusion of (changed) behavior have commonly been researched separately (Chen et al., 2012; Jain et al., 2013; Ekpenyong et al., 2014; Azar and Menassa, 2015). However, Jensen and Chappin (2014) have shown that interactions of device diffusion and behavior diffusion, coined *co-diffusion of technology and behavior* can induce effects that become only visible from the holistic perspective.

Assessing the overall effect of feedback devices beyond single households can be achieved by simulation modeling. This can be done by integrating the above outlined processes into one model. Agent-based modeling has been used successfully for this integration (Jensen et al., 2015), because it allows direct modeling on existing empirical and theoretical knowledge (van Dam et al., 2012). This previous modeling approach should be refined into a more empirical-based model, in order to allow a realistic assessment of the magnitude of the impact of feedback devices.

In this paper, we therefore assess the impact from the 'CO_2 meter' via an empirically-based agent-based model (ABM) that integrates feedback effect and the diffusions of technology and behavior. To support practical applications with more insight, also the contributions of sub-processes to this impact are quantified. This

[1] Practicing SV can also consume more energy, e.g. compared to not ventilating rooms at all.

aims to answer the following question: *what is the overall effect of the 'CO_2 meter' on energy-efficient heating behavior, as emerging from its sub-processes of feedback effect, technology diffusion and behavior diffusion?* The remainder of this paper is structured as follows. First, the functioning of behavior-changing feedback devices is explained, using the example of the 'CO_2 meter'. Second, the framework used to analyze the effect of this device in a multi-household setting is described. Third, a novel simulation model is introduced that projects the potential future impact of the 'CO_2 meter' on heating behavior within the city of Bottrop, Germany. This model is developed and calibrated based on empirical research conducted by some of the authors. [2] Finally, simulation experiments are analyzed in order to answer the stated research question.

3.2. BACKGROUND

In this section is presented how the 'CO_2 meter' affects behavior of its users. Further, it shows how it unfolds its overall effect in a multi-household setting.

3.2.1. FEEDBACK EFFECT OF DEVICE TO ITS USERS

The success of the 'CO_2 meter' in reducing heating demand bases on its relative advantage[3], perceived by its users, and on its conscious and its pre-conscious influence on them.

Use of the 'CO_2 meter' is motivated by its assistance to improve indoor air quality as a means to health and air quality comfort, which has a relative advantage over manual ventilation without knowing CO_2 levels. Previous research showed that a 'CO_2 meter' can change behavior and improve indoor air-quality significantly (Geelen et al., 2008). As the focus of ventilation during the heating period lies mainly on thermal comfort (Griffiths and Eftekhari, 2008; Santamouris et al., 2008), feedback can shift this focus towards air-quality. Energy savings from incentivized SV behavior are a positive side-effect to this, which can additionally motivate use of the device.

A feedback device, such as 'CO_2 meter', can influence the heating behavior of its users (Jensen et al., 2015) via two routes: (1) *via information* it persuades users to start and to stop ventilation. Even though households can be aware of air quality, additional information can lead to reinterpretation and thus to conscious and intentional behavior change. (2) *via supporting habituation* of changed ventilation behavior. *Habits* are action sequences triggered by environmental cues and performed without significant deliberation. Repeatedly practicing a habit with positive outcome increases its strength, making it self-reinforcing and relatively stable (Jager, 2003). Combining the two routes of information provision and support of habituation, new habits would form starting from initially conscious interactions with the feedback device which are then more and more enacted without extensive deliberation. For example, keeping track of exact CO_2 levels would convert into the habit of ventilating for a certain amount of time at certain times of the day, e.g. after getting up in the morning. Thus, habit formation could stabilize the behavior induced by the 'CO_2 meter'.

[2] This refers to the authors of the published journal paper. Model development and calibration was taken out exclusively by the author of this thesis.

[3] Relative advantage is *"the degree to which an innovation is perceived as better than the idea it supersedes."* (Rogers, 2003, p. 15).

However, the empirical evidence about long-term effects of feedback-devices is mixed. Some research suggests that behavior change from feedback devices relapses eventually (Peschiera et al., 2010). Conversely, others suggest conditions under which behavior relapse does not take place, e.g. if reoccurring feedback is intuitive (Jain, 2013), or if coming from a permanently installed device (Burchell et al., 2014). Also, ongoing behavior change has been observed at particularly long-term exposure to feedback devices (Stromback et al., 2011). Due to these contradicting findings, the long-term effect of the 'CO_2 meter' on users can not be clearly deduced from experience with other feedback devices. Therefore, feedback effect was modeled to be neither relapsing, nor increasing, but to be constant over time.

3.2.2. OVERALL EFFECT OF FEEDBACK DEVICE

Figure 3.1 shows how the overall effect of a feedback device emerges from interactions between individual households, based on an assessment framework by Jensen et al. (Jensen et al., 2015). Besides behavior change from feedback devices, central entities of this framework are households who make two decisions: whether to adopt a feedback device and whether to practice SV behavior.

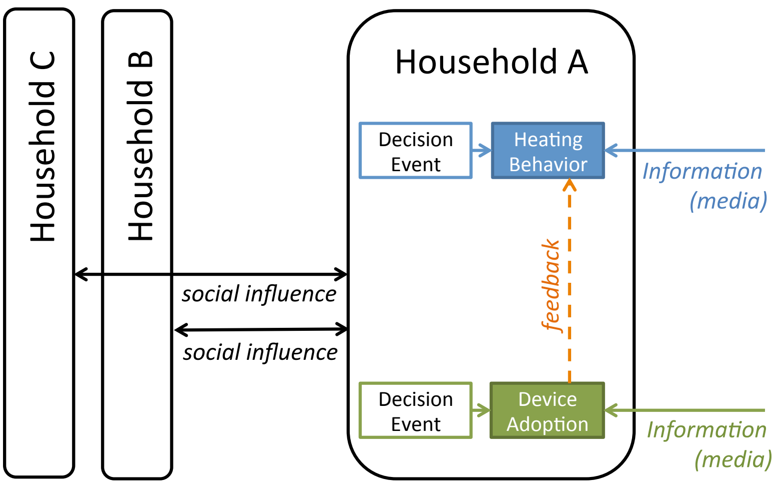

Figure 3.1: **Conceptual framework on the effect of behavior-changing feedback devices.** Each of the three shown households (A, B and C) has two roles: to decide on device adoption (bottom level) and on heating behavior (top level). These decisions are influenced by media information and social influence. Those households that adopt a feedback device are also affected in their heating behavior by feedback from the device.

At 'decision events', households decide on the adoption of feedback devices and on which heating behavior to practice—but they do not decide on it continuously. For device adoption, there are certain windows of opportunity, e.g. when the device becomes available or when previous technology is replaced. Similarly, households do not continuously deliberate on heating behavior. Daily repeated behavior is commonly habitual, which limits its re-evaluation—and thus potential intrinsic behavior change—to sporadic events. Due to the relative stability of habits (Jager,

2003), external events are ideal to trigger the breaking of a habit. In the context of ventilation behavior, such triggering events can be changes of heating costs, household demographics, the place of living, or the appearance of mold within the home. Such events can ‘unfreeze’ a habit environment, create a window of opportunity for conscious deliberation and behavior change, and—via anew habit formation—‘refreeze’ into a (potentially changed) habit (Lewin, 1947).

Once a decision event occurs, the actual decisions on adoption of devices and SV behavior depend on both intrinsic factors of households and their environment. According to the Theory of Planned Behavior[4] (Ajzen, 1991), adoption depends on the intention to do so, and intentions depend on the households’ *attitudes* towards the adoption choice, their *perceived behavioral control* over adoption and the *subjective norm*, i.e. the perceived adoption prevalence within their social environment. We propose information to have the potential to change attitude (i.e. persuading to adopt) and therefore to have an influence on adoption decisions. The importance of subjective norms (Nolan et al., 2008) motivates considering interactions in social networks and the effect that adoption behavior of peers has on a particular household. The perceived behavioral control of households is assumed to be high, as ventilation behavior can easily be changed.

The two diffusions of technology and behavior are connected by the effect that a feedback device has on heating behavior of a household. The diffusion of a feedback device can change the behavior of device adopters. This changed behavior can then influence social norms in the social network of the adopting household. Through this change in norms, the energy-efficient behavior can further diffuse among households, including to households that are either not using the feedback device or that are not influenced by it (Jensen et al., 2015).

3.3. METHODOLOGY

In this section, first, the use of agent-based modeling for our study is motivated. Thereafter, the simulation model developed to answer the research question is presented.

3.3.1. AGENT-BASED MODELING

Agent-based modeling is a bottom-up simulation method. Agents are computer-objects that can correspond *one-to-one* to real-world entities (van Dam et al., 2012). Thus, an ABM can represent households with *“agents [that] are programmed to interact in the same ways as the real actors do and to experience the same constraints and have access to the same knowledge”* (van Dam et al., 2012, p. vi). Consequently, relevant empirical data (e.g. on households’ locations and their decision preferences concerning innovations) can be incorporated into models without the need for further simplification or abstraction. This has the added advantages of making behavior of agents relatively easy to understand and to communicate.

Agent-based modeling is suited to model the diffusion of innovations. According to Rogers, *“diffusion is the process by which an innovation is communicated through certain*

[4] This theory is widely applied for decision modeling (Schwarz and Ernst, 2009; Sopha et al., 2013).

channels over time among the members of a social system" (Rogers, 2003, p. 11). Thus, diffusion strictly depends on decisions and communication of households (van Dam et al., 2012, pp. 48). An ABM, facilitates understanding the mechanisms of emergence, by capturing both an emergent phenomenon and its causing elements

For three reasons agent-based modeling is suitable to capture the overall effect of the 'CO_2 meter'. Agent-based simulation modeling is particularly suited to model household behavior appropriately when their adaptiveness, heterogeneity and local interactions should be accounted for (Grimm and Railsback, 2013). *Adaptiveness* is important to consider, e.g. because households that use feedback devices choose differently on behavior adoption than those that do not; *heterogeneity* is important because households adopt sustainable household products and heating behavior under different conditions; *local interactions* should be modeled due to the role of social contacts in persuading innovation adoption.

3.3.2. MODEL DESCRIPTION

The purpose of the presented model is ex-ante assessment of the 'overall effect' of behavior-changing feedback devices: their effect on heating behavior in the adopting households, the diffusion of these devices, and the diffusion of this behavior change to other households, including non-adopters. The model was implemented in Repast Simphony for Java (North et al., 2013). In the following, it is is presented in the format of an ODD Protocol (Grimm et al., 2010), which is a standard for presenting agent-based models.

ENTITIES, STATE VARIABLES AND SCALES

Household agents are the main model entities. Their properties and actions are shown in Figure 3.2.

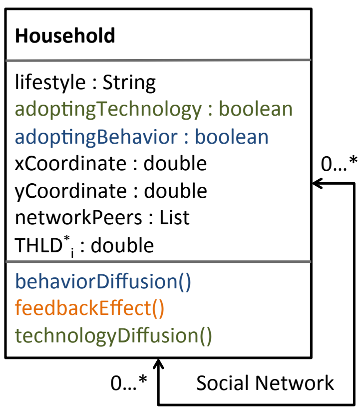

Figure 3.2: **Modeled household properties and actions.** Formatted as a Unified Modeling Language class diagram. See text for details.

Each household agent has six individual properties. Their *lifestyle* (i.e. the consumer group they belong to) is a fixed property of each household that influences their

inclination to adopt sustainable household devices (Schwarz and Ernst, 2009). Whether they adopt a feedback device or SV behavior, respectively, are binary states of each agent (*'adoptingTechnology'* and *'adoptingBehavior'*). They further possess a geographical location (*'xCoordinate'* and *'yCoordinate'*). They are also located in a social network, being influenced by a fixed set of peers (*'networkPeers'*). Each agent has a threshold above which it intends to adopt SV behavior. The threshold is modeled as the minimum fraction of peers that adopted SV behavior (THLD_i^*, see 3.3.2).

Agents perform actions (i.e. *'behaviorDiffusion()'*, *'technologyDiffusion()'*, and *'feedbackEffect()'*) that correspond to the submodels described in sections 3.3.2–3.3.2.

Each simulation step corresponds to one month. The point in time of initialization (t_0) represents January 2006. Feedback devices are introduced in January 2016 (t_{int}) and simulations terminate with the year 2030 (t_{end}). This describes a situation where feedback devices are not known or not available until beginning of 2016. From that moment on, the devices are available on the market.

3

PROCESS OVERVIEW AND SCHEDULING

An overview of the simulation phases and their scheduling is given in Figure 3.3. Simulation is subdivided into three phases: (1) during the *Setup* phase, model runs are initialized (see 3.3.2), household agents are added to the model and connected via a social network (see B). (2) In the *Pre-introduction* phase, feedback-devices are not yet introduced into the system. Thus, the simulation is running but only the process of *behavior diffusion* takes place (see 3.3.2). This serves for the replay of historic behavior diffusion patterns (see 3.3.2). (3) The *Post-introduction* phase starts at the introduction of feedback devices into the system. From there on, also the processes *technology diffusion* and *feedback effect* occur (see 3.3.2 and 3.3.2).

INPUT DATA

Fundamental empirical input data of the model describe households and their social network. 31.839 household agents were generated from municipal geo-data within the spatial extent of the central neighborhoods of the city of Bottrop, Germany. To reconstruct the socio-spatial structure of households in this area (Ernst, 2014), marketing data on the spatial distribution of lifestyles was used to assign each household to a Sinus® *lifestyle group* (Sinus Sociovision, 2015)). This typology clusters households in lifestyles (the so-called *milieu*) which are differentiated along two dimensions: social status and openness of basic values.

The social network between agents was generated based on a mixed-methods social network analysis (Prell, 2011; Holstein and Straus, 2006) conducted in Bottrop. Interviews were conducted in which social network graphs were generated that mapped by which organizations and individuals the interviewees were influenced in their heating behavior, e.g. how to set up their heating system and advice on saving energy. This identified social influence from peers (i.e. friends, neighbors and relatives) as important factors to explain heating behavior. The modeled social network was tailored to feature the same degree-distribution[5] of ego-networks as these empirical networks.

[5]The degree distribution in a graph is the probability distribution of the number of connections that its nodes have.

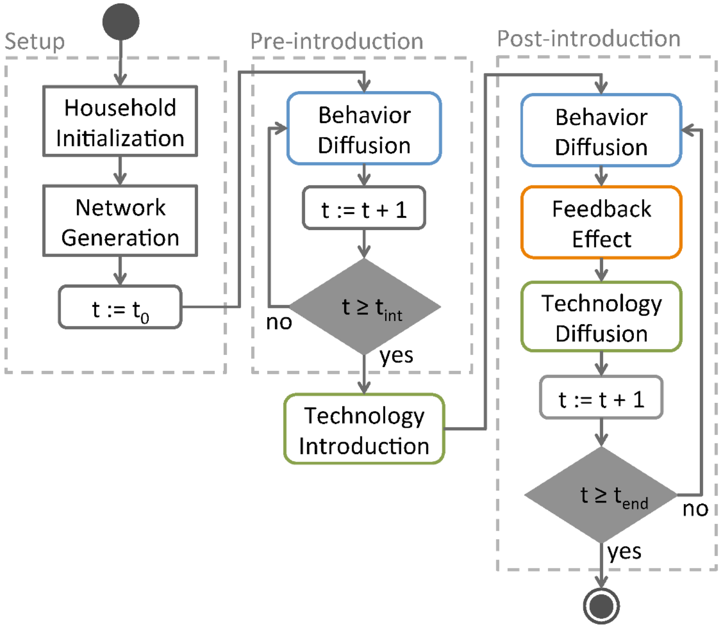

Figure 3.3: **Simulation phases and scheduling.** Formatted as a Unified Modeling Language activity diagram. See text for details.

We furthermore used data on social influence between lifestyles to specify the model network. In particular, the probability that actors of particular lifestyles connect differs between lifestyles (Holzhauer, 2015, Fig. 3.8). See B for how input data was processed in detail.

INITIALIZATION

At initialization, each agent is assigned a subjective norm threshold ($THLD^*_i$)[6]: if the ratio of SV adopters among an agent's peers exceed this threshold, it intends SV adoption (see 3.3.2). The assigned value is randomly sampled from a normal distribution with the parameters $THLD^*_{mean}$ as mean and $THLD^*_{std}$ as standard deviation, which were not modeled as lifestyle specific due to lacking empirical data.

No household adopts feedback technology at initialization ($p(\alpha_{i,t_0} = 1) = 0$). Initial SV adoption ($p(\beta_{i,t_0} = 1)$) is randomly varied between 27–39% of all households, based on the interpretation of a survey in the Ruhr Area from 2006 (Hansmeier and Matthies, 2007). Initial SV adopters are selected from the pool of those households who intend SV adoption according to their $THLD^*_i$ value. If no further intentional adopter is available, another random agent (independently from its lifestyle) is chosen.

SUBMODEL BEHAVIOR DIFFUSION

The behavior diffusion submodel consists of a triggering decision event that initiates a decision on behavior adoption and an adaptation decision model.

[6]See Table 3.1 for an overview of all parameters.

Decision event Events triggering behavioral change are highly specific to personal lives and no empirical data on statistical distribution of such events was available to us. We therefore used Google search frequency on SV behavior as a proxy. Search for information is an integral step of innovation adoption (Rogers, 2003). Monthly frequencies of search engine queries about SV were used as a proxy for events of deliberation on whether to adopt SV behavior. These data were used to parameterize a time-dependent rate $\delta_\beta(t)$, which represents the rate of deliberation on SV adoption in our model (see C).

Adoption decision model The development of the decision model was guided by a qualitative survey, distributed to households in the Ruhr Area in winter 2014/2015. Householders were asked which sources (1) they had received *information* on SV from and, (2) provided they practiced SV behavior, which sources had *motivated adoption*.[7] Responses were quantified by counting the occurrence of answer options for the two questions. Survey results underlined the importance of modeling both media and social contacts to influence behavior adoption. According to our analysis (see D), reported adoptions were motivated for up to 23.1% by social influence and for at least 76.9% by information (from media and social contacts).

This contribution of information and social influence to SV adoption led us to apply the Theory of Planned Behavior for a decision model on the intention to adopt SV behavior. This theory is useful here, because it distinguishes between changes to attitude (e.g. due to information), as well as to subjective norms (e.g. due to social influence). The structure of the applied decision model based on the Theory of Planned Behavior is shown in Eq. 3.1: when deliberating, agent i adopts technology if attitude (ATT_i), perceived behavior control (PBC_i) and subjective norm (SN_i) outweigh an intention threshold (THLD_i). This threshold represents alternative behaviors that have to be exceeded in utility, as well as potential inertia, e.g. caused by the effort of changing behavior.

$$adoption = \begin{cases} 1 & \mathrm{ATT}_i + \mathrm{PBC}_i + \mathrm{SN}_i \geq \mathrm{THLD}_i \\ 0 & \text{else} \end{cases} \tag{3.1}$$

For parameter reduction, we simplified the adoption condition to make it depend only on SN_i (see Eq. 3.2). Thus, subjective norm remains the only dynamic parameter: its exceedance over a threshold (THLD_i^*) expresses intention to adopt SV.

$$\begin{aligned} \mathrm{ATT}_i + \mathrm{PBC}_i + \mathrm{SN}_i \geq \mathrm{THLD}_i &\quad \Leftrightarrow \\ \mathrm{SN}_i \geq \mathrm{THLD}_i - \mathrm{ATT}_i - \mathrm{PBC}_i &\quad \Leftrightarrow \\ \mathrm{SN}_i \geq \mathrm{THLD}_i^* & \end{aligned} \tag{3.2}$$

To capture the role of information in motivating adoption, each agent's attitude towards SV (ATT_i) is incremented each simulation step by $\Delta_{\beta,ATT}$. This represents persuasion from government and media campaigns that provide positive information on SV behavior (Galvin, 2013). Thus increased attitude equals decrementing the threshold

[7]Answer options included mass media, social media, colleagues and classmates, family and household members, friends and acquaintances, and a blank text field for other sources.

$THLD_i^*$ that the subjective norm has to exceed for the decision model to favor SV adoption.

SUBMODEL TECHNOLOGY DIFFUSION

Because the 'CO_2 meter' is relatively novel, no historical adoption shares are available. For estimating diffusion in such cases, Rogers (2003) recommends: (1) transferring knowledge on adoption (e.g. adoption rates) from a similar innovation and (2) surveying perceived attributes of the novel innovation. We combined these approaches by using an existing simulation model on the diffusion of similar technology and by integrating surveyed perceived attributes of the 'CO_2 meter' into this model.

The existing model that was used for this purpose is the technology diffusion model presented by Schwarz and Ernst (2009). It was built to model the diffusion of water-saving shower heads. This device is similar to the 'CO_2 meter', regarding Rogers' generalized innovation characteristics: (1) *compatibility:* just like heating feedback devices, they are integrated in daily household routines to conserve thermal energy (e.g. hot water); (2) *complexity:* installation of both technologies is simple and can be done by the lay person; (3) *triability:* given their similar costs at mass production and their similar complexity of installation, both innovations can be experimented with on a limited basis.

The Schwarz & Ernst model captures households in their heterogeneity in lifestyles. Households—depending on their lifestyle—have different empirical-based decision models on feedback device adoption, each inspired by the Theory of Planned Behavior. Households with lifestyles of higher social status are modeled to deliberate rationally, weighing all adoption decision factors. Conversely, other households decide by *bounded rationality*, based on the subjectively most important decision factor that clearly favors acceptance or rejection of adoption.

After empirical parameterization, the decision model by Schwarz & Ernst is equivalent to the following simple decision rules. At the monthly probability (δ_α) of 0.4%, agents decide on device adoption—this probability was taken over and thus the temporal pattern of how the proxy technology diffuses. At deliberation, the households of higher social status (grouped hereupon as *Social Leaders*) always adopt the diffusing device—not being influenced by social status. Households of the societal mainstream and conservative lifestyles (grouped hereupon as *Mainstream agents*) adopt devices at 50% probability, imitating the adoption choice of the majority of their social network peers otherwise. Households of the hedonistic lifestyle (defined as the social group of relatively high openness of basic values and lower social status (Sinus Sociovision, 2015), labeled hereupon *Hedonists*) exclusively imitate the majority of their peers. Consequently, the latter two lifestyle groups are modeled to be able to discontinue the use of the 'CO_2 meter'.

For adaptation of the model to our case, we surveyed the perception of householders in Germany towards the 'CO_2 meter'. Resulting values of perception substituted the device-specific parameters in the decision model of Schwarz & Ernst. However, the resulting simple adoption heuristics (and consequently the adoption rates and timelines) did not change with these changed parameters. This supports the proposed similarity between the water-saving proxy technology and the 'CO_2 meter', but also reflects the low parameter sensitivity of the applied decision model.

SUBMODEL FEEDBACK EFFECT

We based modeling of how feedback technology affects ventilation behavior directly on observations from living lab experiments in 12 households. These were equipped with a 'CO_2 meter' and their indoor air-quality, heating temperature and energy consumption were monitored. Adopters of the 'CO_2-Meter' were observed to be persuaded to adopt SV behavior at a probability of 0.83 (p(α^*)). This probability was used to model the rate by which households adopt their behavior after having adopted a feedback device. As was the case in the field tests, this effect is modeled to take place within one month after adoption (i.e. one time step after device adoption, cf. Fig. 3.3). As a result from the air-quality feedback, individual households saved more than 10% (supposedly because they were ventilating rooms permanently before) or even increased their energy consumption more than 10% (supposedly because they barely ventilated rooms before given the feedback). Energy savings however concentrated in the interval between 5% to 10%. Given this range of the dominant group, the households with a change in energy consumption of less than 5% were assumed to not having responded to feedback devices significantly, and model them to have not changed behavior.

MODEL VERIFICATION

The model implementation was verified to assure it corresponded to the here presented conceptual model. Verification focused on the two submodels *behavior diffusion* and *technology diffusion*, being the most complex model components. The behavior diffusion submodel was verified by unit testing of its implementation. The technology diffusion model was verified by *reproduction*: given the same parameterization, but different households and social network, technology diffusion was highly similar to results of the technology diffusion model by Schwarz and Ernst (2009), as shown by Jensen et al. (2015).

PARAMETERIZATION

Table 3.1 shows the model parameters set during initialization. Four parameters were varied in 5 steps each, equally spaced within the given intervals. Each of the resulting 625 parameter combination was simulated twice—once with and once without the 'CO_2 meter' being introduced.

Indirect calibration Whereas the feedback effect and technology diffusion processes were modeled on living lab experiments and an existing model, we indirectly calibrated the behavior diffusion process with three empirical patterns. This procedure of parameter uncertainty reduction is also referred to as 'pattern-oriented modeling' or 'inverse modeling' (Grimm et al., 2005; Wiegand et al., 2003). In a first step, those parameter combinations that reproduce the empirical patterns are identified, and only these combinations are subsequently used for evaluating the effect of feedback devices. This assures that results accord to the available empirical data.

First, the conducted survey revealed a pattern on the respondents' perceived ratio of peers who adopted SV behavior. At the beginning of 2015, its value is 38.3%, which was extended by an uncertainty range to the interval 32.3–44.3% .

Second, the surveyed ratio between information and social influence in motivating SV adoption (see Table C.1) was applied. Modeled SV adoptions (up to the time of the

3

Table 3.1: **Parameterization** for the simulation experiments. See text for references to parameterization sources.

Parameter	Value	Meaning
$p(\beta_{i,t_0} = 1)$	[0.27, 0.39]	Initial SV behavior adoption share
$THLD^*_{mean}$	[0, 1]	Mean of behavior adoption threshold
$THLD^*_{std}$	0.3	Std. of behavior adoption threshold
$\delta_{\beta,event}$	]0, 0.04]	Rate of behavior delib. trigger events
$\Delta_{\beta,ATT}$	]0, 0.006]	Monthly increment to attitude towards SV
$p(\alpha_{i,t_0} = 1)$	0	Initial feedback device adoption share
δ_α	0.004	Technology adoption deliberation rate
$p(\alpha^*)$	0.833	Success rate of feedback devices
t_0	0	Time step (month) of initialization
t_{int}	120	Time step (month) of device introduction
t_{end}	300	Time step (month) of end of simulation
d_{NBHD}	200	Max. length (m) of neighborhood edges
p_{NBHD}	0.5	Ratio of edges within neighborhood

survey, i.e. 2015) was traced back by whether they were caused rather by change of attitude or subjective norm. If a household agent (until first SV adoption) underwent more change in attitude than in subjective norm, then this agent was assumed to be ‘motivated’ by information. Conversely, if change in subjective norm exceeded that of attitude, the behavior change was assumed to be ‘motivated’ by social influence. Thus, those parameterizations were selected that generated the surveyed shares of adoption motivation (i.e. ca. 8–23% from social influence and ca. 77-92% from information, until the beginning of 2015; see D).

Third, those initializations where less than half of initial SV adopters adopt this behavior intentionally were discarded. This represents a tendency towards initial adopters to intend SV adoption, without enforcing full intentionality.

3.4. RESULTS AND DISCUSSION

To address the research question on the overall effect of feedback devices on ventilation behavior, we conducted the following four model experiments. (1) A reference scenario of behavior diffusion, where feedback technology is not introduced. Thereby, model parameterizations that reproduced empirical patterns of SV behavior diffusion (see 3.4.5) were selected and only those were included for the following scenarios. (2) The diffusion of the ‘CO_2 meter’ only was simulated. (3) The *co-diffusion of technology and behavior* was simulated, in which diffusing feedback devices add to and reinforce the diffusion of SV behavior. (4) In concert with the baseline behavior diffusion from experiment 1, diffusion of devices among households where they can change behavior was simulated. But this behavior change from devices was assumed not to diffuse beyond adopting households. Results from this experiment were compared to experiment 3 to quantify relative strengths of technology diffusion and behavior diffusion from feedback devices.

3.4.1. EXPERIMENT 1: BEHAVIOR DIFFUSION

To calibrate the diffusion of SV behavior at absence of feedback devices, those parameterizations were selected that met the given empirical patterns.

Parameter selection This section shows how application of empirical data from interviews decreased parameter uncertainty about the varied parameters $THLD^*_{mean}$, $\Delta_{\beta,ATT}$, $\delta_{\beta,event}$, and $p(\beta_{i,t_0}=1)$. These have the following effects in the model: (1) $THLD^*_{mean}$ influences whether, during the course of the simulation, SV adoption had the tendency to diffuse successfully or is successively rejected; (2) $\Delta_{\beta,ATT}$ influenced the same feature, but could only add positively to SV behavior diffusion. Thus, it can reverse a negative trend caused by a high $THLD^*_{mean}$. (3) $\delta_{\beta,event}$ controls the speed of behavior diffusion, e.g. a higher rate increased (negative or positive) rates of diffusion in magnitude. (4) $p(\beta_{i,t_0}=1)$, i.e. initial SV adoption share, influences which parameter combination could meet the surveyed adoption share pattern in 2015. At lowest SV initialization, exponentially increasing runs were selected. Conversely, at highest SV initialization, runs with a quasi-linear decline in SV adoption were selected.

Fig. 3.4 contrasts the state space of behavior adoption over time between all simulated parameterizations and the 7% of parameterization sets that were selected via the empirical patterns. Behavior diffusion trajectories of all model parameterizations were diverse, with SV adoption exceeding 95% and dropping below 5% over the course of simulation. Conversely, the state space of the selected parameterizations narrowed down significantly. Variation is particularly low until 2016, which is up to when empirical data was available.

Hence, the empirical patterns reduced uncertainty the most at the time period they apply to, but still reduced uncertainty considerably for the simulation time from 2016 on. The gain of SV adoption over the course of the simulation had a strong positive tendency, ranging from ca. -15% to ca. +60% over the same time period. Thus, the range between moderate decrease to drastic increase projects a positive expectation for future SV adoption.

Distribution under selected parameterizations SV behavior in selected model variants is shown in Fig. 3.5. Despite their variation of up to 60%, half the selected model variants, as well as the average adoption per time step, lay within a relatively narrow band of c. 20% difference in SV adoption share. Distribution of projected SV adoptions was skewed: outliers towards lower SV adoption were stronger than towards greater ones.

3.4.2. EXPERIMENT 2: 'CO_2 METER' DIFFUSION

Fig. 3.6 shows simulated adoption of feedback devices among different lifestyle groups over time. Device adoption rates differed between lifestyle groups: agents of the Leading Lifestyles showed highest, the Mainstream group intermediate, and Hedonists lowest adoption rates. This was directly caused by different adoption decision models (see 3.3.2).

Due to this difference in decision models, SV adoption curves differed between lifestyles: Leading Lifestyles showed an *asymptotic*, Mainstream agents a *quasi-linear*,

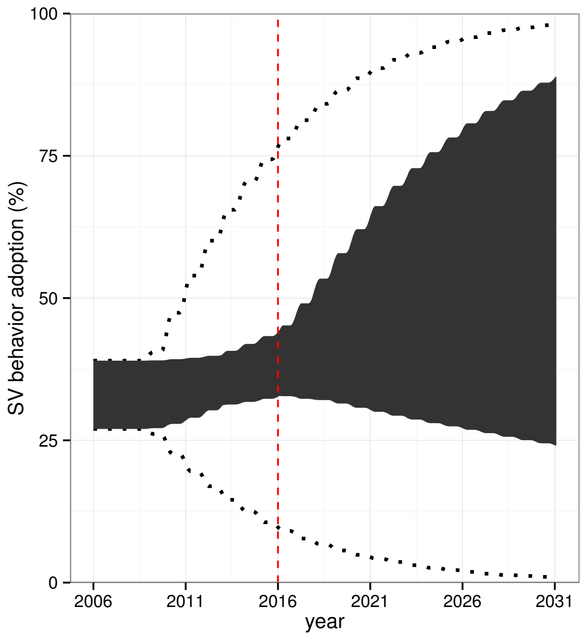

Figure 3.4: Pattern-oriented selection of parameterizations. The dotted lines delimit the state space of all simulation runs. Range of selected parameterizations shown by black area. Curve oscillation was due to seasonal variation in SV adoption deliberation (see C.4). The dashed vertical line highlights the point in time before which empirical patterns were available.

and Hedonists an *exponential* increase in adoption. SV adoption increased asymptotically among agents of the Leading Lifestyle, because they always decide to adopt the 'CO_2 meter' when deliberating on adoption. This caused successive convergence against an asymptote of 100% device adoption. Conversely, Hedonists are imitating their peers, causing a successively growing rate of adoption due to an increasing overall device adoption. For mainstream agents, who mix both these decision strategies, showed a quasi-linear adoption curve, which is likewise a mix of the two previous adoption curves.

3.4.3. EXPERIMENT 3: CO-DIFFUSION OF TECHNOLOGY AND BEHAVIOR

In this experiment, behavior diffusion and technology diffusion were integrated to a co-diffusion of technology and behavior (i.e. the simultaneous diffusion of feedback devices and SV behavior).

In Fig. 3.7, its adoption under sole behavior diffusion (scenario 1) was compared to *co-diffusion of technology and behavior* (scenario 3). The co-diffusion scenario resulted in greater average SV adoption, compared to scenario 1. Due to feedback devices, SV adoption increased by ca. 12 percentage points ($\sigma = 5.3$).

In Fig. 3.8, the role of different technology adoption shares across lifestyle groups on their SV adoption is examined. The magnitude of additional SV adoption of lifestyle groups followed their device adoption: Leading Lifestyles showed greatest additional

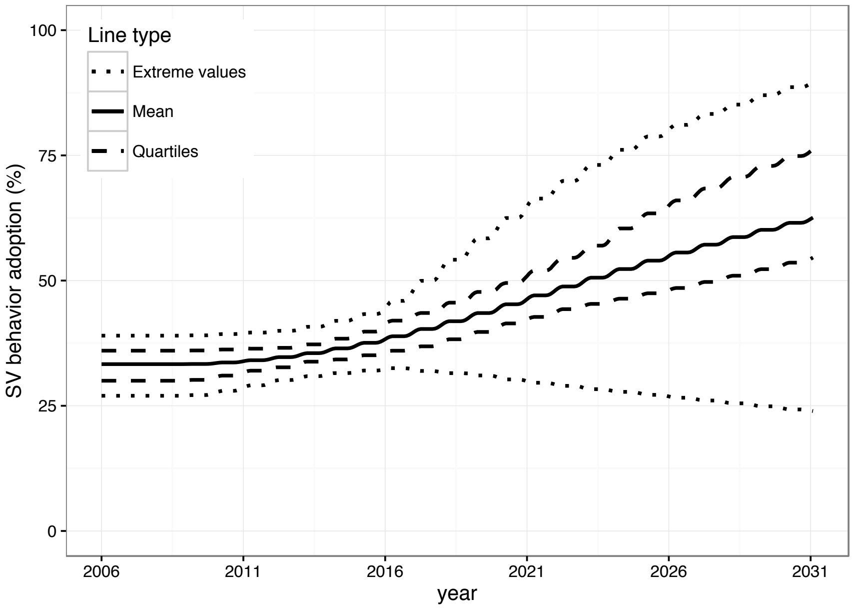

Figure 3.5: Distribution of model runs with selected parametrization. The dotted lines delimit the state space of all selected parameterizations. The dashed lines delimit the state space between the 25th and 75th percentile at each time step. The continuous line represents the expected value (mean) of SV adoption per time step. Curve oscillation was due to seasonal variation in SV adoption deliberation (see C.4).

3

adoption, Mainstream agents intermediate, and Hedonists lowest deviation. Thus, affinity of a lifestyle to adopt the 'CO_2 meter' considerably influenced the overall relative effect that the device had on the lifestyle's SV adoption.

Energy-efficiency impact To illustrate the energy-related impact of the 'CO_2 meter', these results on additional SV adoption were transformed into change of heating energy demand. As the living lab experiments showed, those device adopters who changed their energy consumption after adoption significantly (see 3.3.2) decreased their energy consumption by an average of 8%. The empirical reduction in energy demand from SV behavior was therefore approximated as these 8%, which lies within the range of energy savings previously theorized (Galvin, 2013).

On this basis, the difference between experiments 1 and 3 of up to 18% additional SV adopters of the Leading Lifestyles 15 years after device introduction translate into ca. 1.5% additional heating energy savings in this group. Analogously, Mainstream Lifestyles would decrease energy demand by ca. 1%, and Hedonists by ca. 0.5%. Hence, the facts that the 'CO_2 meter' is only adopted partially and that SV diffusion would spread independently from feedback devices anyway considerably lower the overall effect of the CO_2 meter on the multihousehold level, compared to the 8% of potential energy savings of a single household. This lower effect, however, still appears attractive given

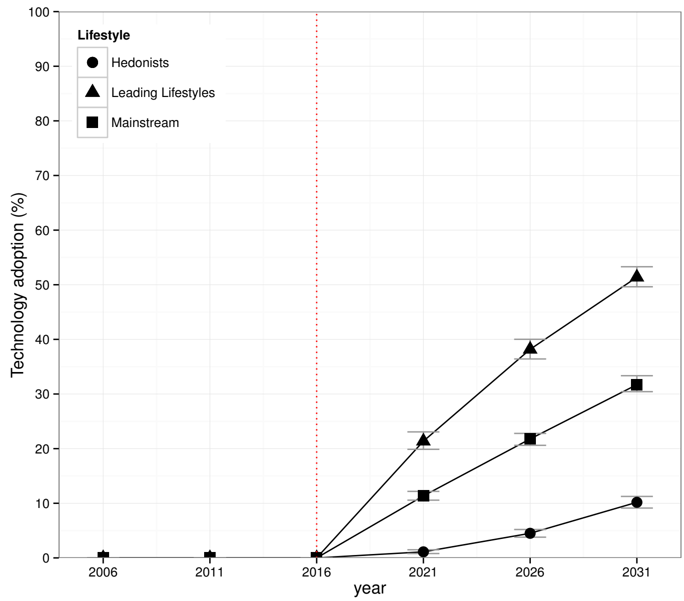

Figure 3.6: Simulated technology adoption over time, differentiated by lifestyle groups (i.e. Social Leaders, Mainstream and Hedonistic Lifestyles in top-down order). The dashed vertical line highlights the moment when feedback devices are first introduced.

the relatively low costs for the 'CO_2 meter' in comparison to its alternatives, e.g. energy efficiency renovation.

3.4.4. EXPERIMENT 4: QUANTIFYING SUB-PROCESSES

The fourth model experiment aimed to quantify the relative contributions of technology diffusion and behavior diffusion to the overall effect of the 'CO_2 meter'. While it is obvious that the devices themselves need to diffuse in order to unfold an effect on the multi-household scale, it seems less obvious that diffusion of behavior induced by the devices will make a significant difference. The potential for such a significant contribution of behavior diffusion to the overall effect of feedback devices was shown by previous research (Jensen et al., 2015), but it was not yet quantified. It appears useful for practical applications to know whether to concentrate efforts rather on achieving successful technology diffusion or on supporting behavior diffusion, and hence use our empirically-based model to investigate the issue further.

A fourth experiment was thus conducted, in which technology adoption statically increases SV adoption: it may lead to SV adoption as in the previous experiments, but this change in behavior is considered to remain restricted to the adopting household and not to add to behavior diffusion. Therefore, behavior diffusion unfolds as simulated in experiment 1, unaffected by the diffusion and effect of feedback devices.

To quantify the relative contributions of technology diffusion and behavior diffusion on SV adoption, experiments 3 and 4 were compared in their additional SV adoption

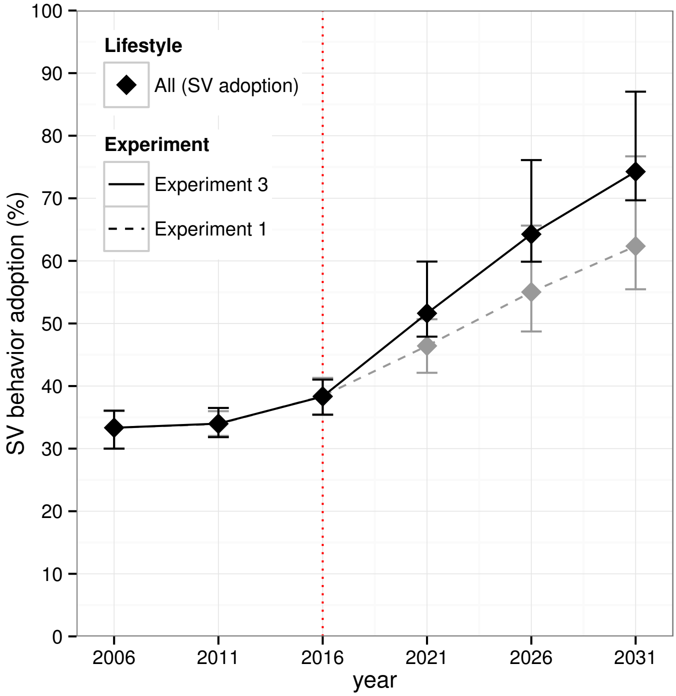

Figure 3.7: Comparing SV adoption shares for all agents between co-diffusion of technology and behavior (solid line) and experiment 1 (dashed line). The dotted vertical line highlights the moment of feedback devices introduction. Whiskers indicate the minima and maxima.

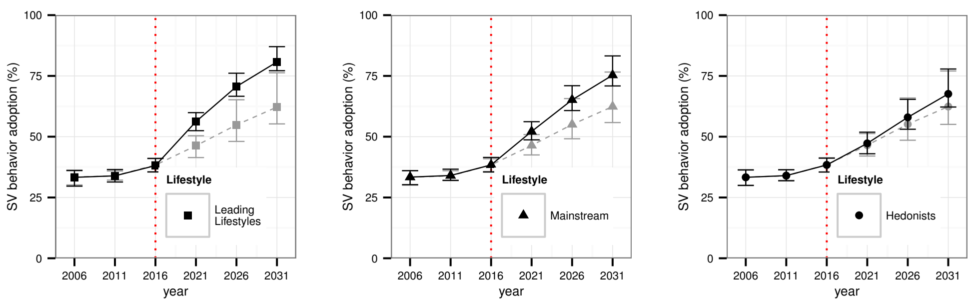

Figure 3.8: Comparing SV adoption shares for lifestyle groups between scenario 1 (dashed line) and co-diffusion of technology and behavior (solid line). The dotted vertical line highlights the moment when feedback devices are first introduced. The whiskers indicate the 25th and 75th percentile.

over the reference scenario from experiment 1. Experiments 3 and 4 thereby only differ in the diffusion of behavior induced by adopted devices.

Shown in Fig. 3.9, experiments are compared between pairs of the same parameterization. It shows the additional effect to non-adopters of feedback devices

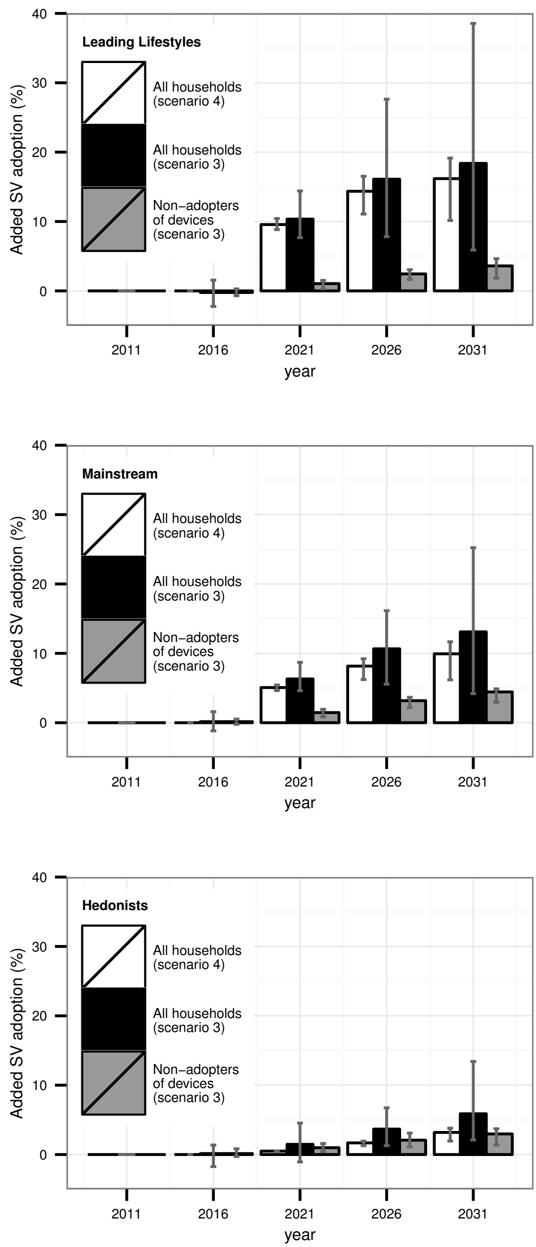

Figure 3.9: Additional percentage points of SV behavior adoption due to feedback devices. Calculation based on comparing SV adoption share between simulation runs at same parameterizations *with* and *without* feedback devices. Added adoption is shown for all agents under the scenarios of *static technology diffusion* and *co-diffusion of technology and behavior* and for those agents who do not adopt feedback devices at the *co-diffusion* scenario. Whiskers indicate 25th and 75th percentiles.

in the co-diffusion scenario[8]. For both experiments—similar to Fig. 3.8—differences for *all agents* in Fig. 3.9 were greatest for Leading Lifestyles, intermediate for Mainstream agents, and lowest for Hedonists. This underlines the importance of different affinities of lifestyles to adopt feedback devices. Added SV adoption steadily increased over time for all lifestyle groups and is always positive after 10 years of device diffusion. As shown in Table 3.2, the overall effect of the 'CO_2 meter' on additional SV adoption by Leading Lifestyles consisted to ca. 12 percentage points of behavior diffusion, for Mainstream agents to ca. 24 pp. and for Hedonists to ca. 46 pp.

Table 3.2: **Summary on the overall effect of the 'CO_2 meter' in percentage points.** Standard deviation shown in parentheses. Further is presented how generation of this effect is composed of technology diffusion and behavior diffusion.

	All households	**Leading Lifestyles**	**Mainstream & Traditional Lifestyles**	**Hedonists Lifestyles**
Added SV adoption (pp)	12 (5.3)	18 (8)	13 (6)	6 (3)
Technology Diffusion (%)	78	82	76	54
Behavior Diffusion (%)	22	12	24	46

This finding is underlined by the additional effect to non-adopters of devices in the co-diffusion scenario. For each lifestyle group, difference in SV adoption in this group increased steadily. Over time, this impact on SV adoption is highly similar between non-adopters of different lifestyle groups, because they were modeled to decide on SV adoption in the same way. This effect to non-adopters (of devices) further adds weight of evidence to the relevance of behavior diffusion in the co-diffusion of the 'CO_2 meter' and SV behavior, e.g. almost half additional SV adoption by *all* Hedonists is as well achieved for Hedonists that are non-adopters of devices. The mechanism by which non-adopters of devices are reached is further discussed by Jensen et al. (2015).

3.4.5. VALIDITY AND LIMITATIONS

In order to achieve a valid assessment of the 'CO_2 meter' from model experiments, the model used for this should adequately reflect relevant aspects of reality. These aspects were selected according to a previously published assessment framework (Jensen et al., 2015). Realism of modeling these was assured by carefully designing the model components technology diffusion, behavior diffusion and feedback effect based on empirical data and widely accepted theory.

To guarantee sufficient realism of the *behavior diffusion* submodel, indirect parameterization (inspired by pattern-oriented modeling (Grimm et al., 2005)) was used to select those parameterizations that successfully reproduce empirical patterns. Patterns regarding (1) SV adoption shares in 2015, (2) motivations to adopt SV, and (3) intentionality of SV adoption at initialization were applied. Selected parameterizations matched all of these three patterns, thus adding weight of evidence to realism of this submodel.

Validation of the *technology diffusion* submodel bases on the TAPAS approach, standing for *"Take A Previous model and Add Something"* (Frenken, 2006). Instead of

[8]Note that for experiment 2, no such additional effect to non-adopters on devices exists.

building a new technology diffusion submodel from scratch, an existing model was 'taken' and other processes were 'added'. This has a key advantage: *"one can take advantage of existing core models to formulate a new robust model in a relatively short amount of time and with a larger degree of understanding"* (Frenken, 2006, p. 152). This also contributes to model validation, particularly if the previous model was successfully validated. The *previous* model here is the technology diffusion model by Schwarz and Ernst (2009), which was validated by being based on survey data and being tested against empirical diffusion data of household products. To assure its correct use in this study, its transferability to the 'CO_2 meter' was justified (see 3.3.2) and its successful re-implementation verified (see 3.4.2).

Realism of the *feedback effect* process directly stems from modeling it on results from living lab experiment. Measurements on the percentage of households who change behavior when using the 'CO_2 meter' and resulting energy savings were integrated into the model.

Limitations We expect the following limitations to have potentially affected our findings: the fundamental uncertainty regarding future innovation diffusion, small sample sizes of empirical data, behavior diffusion modeling decisions, and how technology introduction is modeled.

Results strictly depend on whether the 'CO_2 meter' and SV behavior will diffuse successfully in the future. Due to contingency of the future, perfectly predicting innovation diffusion does not appear to be possible. Instead, modeling what happens if *both diffusions will take place* is possible and useful. The uncertainty of this projection was reduced with empirical data from multiple sources. Additionally, a simulation approach was chosen that can cope with parameter uncertainty, basing findings on the ensemble of all parameterizations that were validated.

Limited empirical data from multiple sources might have affected representativeness of results, e.g. the limited period of time over which the 'CO_2 meter' has been observed in a small number of households. Therefore, the estimated energy savings from SV behavior of 8% could be either under- or overestimated. It should be considered that estimated energy savings (linearly) inherit this added component of uncertainty.

SV behavior choice was modeled to be equal across lifestyle groups. But this might not be the case in reality. Heterogeneity would in principle be possible. Some lifestyles could have an inclination towards certain behaviors, e.g. some could be more motivated to practice energy-efficient behavior; or behavior change might be more inconvenient for others. These options were not considered here here, because no suiting empirical data regarding heterogeneity in behavior adoption was available. Instead the model was built directly on the limited available data.

Further, SV behavior was modeled as binary: households do thus either adopt shock ventilation or not. It would be desirable to model ventilation behavior in more detail, in order to better represent the energy-efficiency related impact of a feedback device. For instance, duration of ventilation could be an important additional factor to consider (Galvin, 2013), including if households do not ventilate at all. Given that our empirical basis did not allow further differentiation, we chose to limit degrees of freedom in the

model to those of available data. Hence, the effect attributed to SV adoption in this paper represents an empirical average difference to other ventilation practices.

Finally, the specific way in which device introduction was modeled to can be expected to impact the results. Technology becomes available quickly and to all agents at the same time. This implies feedback devices to be marketed intensively and successfully. This implication was accepted, because it is the simplest assumption and detailed comparison between marketing strategies is beyond the scope of this paper.

3.5. CONCLUSION

Purpose of this study is to answer the following question: what is the overall effect of the 'CO_2 meter' on energy-efficient heating behavior, as emerging from the processes of feedback effect, technology diffusion and behavior diffusion? This effect was found to be significant, accounting for an average 12% ($\delta = 5.3$) added percentage points of additional SV adoption for the modeled case city Bottrop. For this case area, the 'CO_2 meter' was estimated to be able to decrease residential heating energy demand by c. 1% at 15 years after its introduction.

Overall effect of feedback devices Our simulation results indicate that introduction of the 'CO_2 meter' in the city of Bottrop would significantly increase energy-efficient heating behavior. Results showed the average overall effect of this device for different social groups to range from ca. 6 to ca. 18 percentage points of additional SV adoption at 15 years after device introduction. This magnitude adds weight of evidence to the relevance of the driving key mechanism: the direct effect of feedback to device users was identified as the initial keystone to the effect of devices to SV diffusion. Technology diffusion spreads devices among households (where feedback can then change behavior) and behavior diffusion adds to this by spreading behavior change from adopters to non-adopters of devices.

Neglecting the impact of the 'CO_2 meter' via behavior diffusion would underestimate its overall effect significantly. To indicate which processes would be most relevant in interventions that use the 'CO_2 meter', relative contributions of technology diffusion were compared to behavior diffusion on SV adoption. The share of the overall impact that the 'CO_2 meter' caused via behavior diffusion ranged from 12% for Leading Lifestyles, over 24% for Mainstream and Traditional lifestyles, to 46% for the lifestyle group Hedonists (see Table 3.2). Thus, this underestimation would be the least for households of highest social status, for those of intermediate to low social status and highest openness of basic values.

Effects on heating energy consumption Based on the simulation results, average heating energy savings of ca. 1% could be expected within 15 years from the introduction of the 'CO_2 meter' in the City of Bottrop. This ranges from 1.5% for Leading Lifestyles, over c. 1% for Mainstream Lifestyles and to 0.5% for the Hedonist lifestyle. 1% of energy savings appears rather low compared to the ca. 8% savings potential of the 'CO_2 meter' for individual households. This difference in our assessment was due to the following reasons: (1) ca. 40% of households in the case area are already adopting SV

behavior, (2) SV behavior has—according to our results—the tendency to increase in adoption, independently from feedback devices, and (3) diffusion of the 'CO_2 meter' will likely not reach full penetration in a reasonable time frame. Therefore, describing a feedback device's energy savings potential by its potential for individual households can be misleading. Instead, it appears preferable to use a potential that is scaled by the expected spreading of this device and by the spreading of its induces behavioral change.

Merits of the 'CO_2 meter' in interventions The 'CO_2 meter' will likely differ in acceptance and adoption between social groups; assumed it spreads similarly as other sustainable household products. This difference influences how much these groups would undergo change in heating behavior due to the 'CO_2 meter' and would predominantly affect households of higher social status (i.e. Leading Lifestyles). Hence, the authors recommend this to be considered at interventions that use the 'CO_2 meter': targeting households of higher social status with such interventions could have a greater impact.

The spreading of the 'CO_2 meter' has been identified as the main factor determining its overall impact. Thus, practitioners who want to create impact with this device should primarily support its spreading between households. However, supporting the spreading of behavior change from device adopters is worthwhile, too—particularly when aiming to spread energy-efficient heating behavior to social groups that are less inclined to use the 'CO_2 meter'.

Overall,—considering the uncertainty of technology projections—the 'CO_2 meter' promises significant energy savings at low cost. In comparison to other strategies, it can be distributed cost-effectively and is widely applicable. Thus, this device can be regarded as fit to efficiently tackle 'low hanging fruits' of energy-efficiency in residential heating.

Future research We propose to assess further feedback devices using the integrated modeling approach that is presented here. Additionally, we expect co-diffusion of technology and behavior to have a fruitful role in future behavior change interventions, e.g. to increase overall behavior change.

Further, elements of the model that remained uncertain due to lacking empirical data should be refined based on further empirical research. For instance, further differentiating the exact ventilation behavior that modeled households can practice could be a useful direction of research. Also valuable would be those research designs which observe interactions between technology diffusion, feedback effect and behavior diffusion. Further, linking of separately gathered data sets on the respective processes could improve understanding these interactions.

Regarding technology introduction, policy options regarding the here modeled intervention should be explored, e.g. device marketing strategies. We recommend applying the here presented model to achieve this. This would both deepen insight into the future prospects of feedback devices, as well as support policy decisions in how to apply them effectively.

4

SIMULATING MARKETING STRATEGIES FOR FEEDBACK DEVICES

"...before any new product can be developed it has to be properly researched.
We've got to find out what people want from fire,
how they relate to it, what sort of image it has for them."

Douglas Adams

4.1. INTRODUCTION

To quickly reduce CO_2 emissions, one way that seems promising is to change heating behavior. In the EU, residential buildings account for ca. 30% of final energy consumption; about 60% of this is taken up by space heating (Itard and Meijer, 2008). The potential for the reduction of this share via behavioral changes is 20-30% (Wood and Newborough, 2003), e.g. by practicing energy-efficient ventilation behavior (Galvin, 2013) and setting lower thermostat temperatures (Guerra Santin et al., 2009).

Providing feedback to energy consumers about their energy consumption behavior can help them tap into this savings potential. Feedback about behavior was found to decrease energy consumption up to 20%, with an average of 10% (Karlin et al., 2014; Wood and Newborough, 2003). Numerous approaches exist to give feedback to energy consumers, e.g. email, online platforms, or installed feedback devices (Karlin et al., 2014; Laschke et al., 2011; Darby, 2006). One example of a feedback device is a so-called 'CO_2 meter', which shows the indoor air quality–measured by CO_2 level–in the form of a traffic light. This was shown to be effective in convincing households to practice the energy-efficient 'shock ventilation' (*'Stoßlüften'*) of rooms (see Section 4.2).

This chapter has been submitted to the Journal of Environmental Management.

This study focuses on feedback devices installed in the home, due to their potential to create greater effects in the long term. One challenge to feedback interventions is *behavioral relapse* (Verplanken and Wood, 2006), i.e. energy consumption levels returning to the levels before intervention occurred. However, feedback from devices appears to be less prone to behavioral relapse or decreasing attention for feedback—particularly when installed quasi-permanently and made directly accessible to users (Burchell et al., 2014).

To reduce heating energy demand significantly, market introduction of feedback devices should be managed effectively—and ineffective management should be avoided early on. Especially in the earliest phase of product diffusion, good marketing can significantly support the adoption of that product (Delre et al., 2007). There are various established marketing strategies, such as advertising devices to the general public or giving the first devices away as free promotional gifts. It is critical to identify the best options among such strategies given the requirement of maximum behavior change. We argue the respective merits of each strategy should be well estimated ex-ante—before any real-world implementation. This is crucial to avoid actions that have low or counterproductive effects and would delay achievement of desired results.

4

Simulation modeling is useful for identifying effects of actions on product diffusion before their implementation (van Dam et al., 2012; Schwarz and Ernst, 2009; Rixen and Weigand, 2014). Simulation, being quicker than real-time, can thus help avoid ineffective action in the real world. Simulation modeling is capable of estimating the potential future effects of marketing strategies towards sustainable household products and the resulting impacts (Schwarz and Ernst, 2009; Delre et al., 2010). Yet, such undertaking has to acknowledge the uncertainties of forecasting social systems and the energy sector (van Dam et al., 2012). Therefore, goal of this study is not predicting the exact impact of marketing strategies of great detail. Instead, high-level marketing strategies are merely to be compared in a relative way, regarding their general effectiveness and cost-efficiency.

This study therefore aims to use simulation modeling to compare and propose marketing strategies for feedback devices ex-ante. This assessment will adopt and refine a simulation model on the diffusion and effect of a CO_2 meter (Jensen et al., 2016). From this, we aim to identify the management strategies for rolling out feedback devices that show the best impact over a range of future scenarios. To facilitate practical results, we also suggest stakeholders that would be well suited to putting these devices into action. Altogether, this study addresses the following research question: *Which innovation management is most effective at creating additional energy-efficient heating behavior via the marketing of behavior-changing feedback devices?*

The rest of this paper is organized as follows. First, we present previous findings on the device used in this case study. Second, we present the state of literature on modeling marketing strategies, the specific simulation model adopted for this case study, and the strategies we assess with this model. Third, we answer the research question by simulating and analyzing these strategies.

4.2. THE CO_2 METER CASE STUDY

In this section, we present the CO_2 meter as a case study of a device and previous findings on its effects. This device gives feedback to its users about indoor air quality and gives them an incentive to ventilate energy-efficiently. The device shows its feedback in the intuitive colors of a traffic light: good air quality is shown by green, intermediate by yellow, and unhealthy air by red.

Field tests have shown that the use of a CO_2 meter has the potential to change the ventilation behavior of householders, which consequently supports a reduction in heating demand. For ventilation, most households in Germany have windows that have two sets of hinges that allow the option of opening windows completely (i.e. practicing so-called 'Stoßlüften' or 'shock ventilation') using one set of hinges, or only partially, by tilting them open on the second set of hinges (Galvin, 2013). The CO_2 meter increases the attractiveness of shock ventilation, because this behavior increases the ventilation rate and thus the speed at which improved air quality is shown by the feedback. Increased ventilation rate and avoidance of overly long ventilation times, in turn, reduce heating energy demand (Galvin, 2013). The savings from adopting shock ventilation have been shown to amount to an average of approximately 8% (Lovric, 2015; Jensen et al., 2016).

Previous research assessed not only the effect of the CO_2 meter for its direct users, but for an entire city–comprised of adopters and non-adopters of feedback devices. Impact from the CO_2 meter relied on three processes: (1) its diffusion among households, thus increasing the number of users, (2) the feedback effect for its users, and (3) consequent spread of this induced behavior change, e.g. to households that do not use the device.

4.3. METHODS

This study aims at designing marketing strategies for feedback devices, and then identify which would be most effective. We adopted the four-step method by Roozenburg & Eekels (1995) for this task: (1) analysis of the problem and gathering of existing options to solve it; (2) synthesis of the analyzed options to tentative solutions; (3) simulation of these solutions to forecast *"the behavior and properties of the designed product by reasoning and/or testing models"* (Roozenburg and Eekels, 1995, p. 91); and (4) empirical evaluation of the most promising solutions.

In this study, we focus on the first three of these steps—analysis, synthesis and simulation. Feedback devices for behavior change in heating are still in the early phases of market entry. This study will prepare and support the future real-world evaluation and implementation of marketing strategies of these devices.

4.3.1. ANALYSIS: MARKETING OPTIONS

We analyzed various possible marketing strategies for feedback devices by drawing on the wide base of literature on managing the diffusion of innovations with marketing.

CLASSIFYING MARKETING OPTIONS IN THE LITERATURE

The challenge of getting more households to adopt a product is a problem tackled by the field of marketing. We thus reviewed multiple promising marketing strategies. These strategies were classified in a widely used array of marketing options: E.

Jerome McCarthy's 'marketing mix' (1996). In addition to the product itself and its characteristics—we assume a situation where an already designed device needs to be marketed—the marketing mix classifies actions into three additional categories: (1) The price of the product, on which the willingness of adoption may depend; (2) Promotion activities that communicate the product to potential adopters; and (3) the place, i.e. the distribution channels via which a product is marketed. Motivated by our intention to simulate selected marketing strategies with agent-based modeling, we focused our literature search on this field. Thus, the Scopus database Elsevier (2015) was queried with the search term *'simulation AND agent-based AND diffusion AND innovation* AND (promotion* OR policy).'* The selection criterion for strategies was their reported success. In addition, we included sources in the review article by Kiesling et al. (2012) on this question.

Price The most frequently modeled marketing strategy in the reviewed studies were discounts on products. Successful incentives were found in the form of discounts (or subsidies) (Ferro et al., 2010; Cantono and Silverberg, 2009; Zhang et al., 2015) and purchase bonuses (Rixen and Weigand, 2014); the changing of economic interactions in a system has also been found to be indirectly successful (de Holanda et al., 2008). The overall economic effect of giving away a limited number of products for free may also be greater than if discounts or rebates are offered. This approach has shown particularly promising when compared to discounts (Zhang et al., 2015).

Promotion Regarding product promotion, advertising and social marketing have repeatedly been found to be successful at supporting product diffusion:

(1) Awareness of a product is a crucial precondition to its adoption (Rogers, 2010). Delre et al. (2007) showed that spreading information about a new product–early in its marketing phase–can increase the diffusion success. This is supported by other studies (Rixen and Weigand, 2014; de Holanda et al., 2008; Schreinemachers et al., 2007).

(2) Social marketing is a more focused approach to promotion, in which targeted individuals market to their peers. A particularly positive role in spreading innovations appears to be played by 'Opinion Leaders' (Rogers, 2010). These are people who are considered to be relatively highly innovative (i.e. they adopt innovations earlier) (Rogers, 2010) and who also can influence a large number of other people (Kiesling et al., 2012). Reviews by Kiesling et al. (2012) and Nisbet & Kitcher (2009) and a study by Eck et al. (2011) highlight the merits of leveraging this group in social marketing to managing the diffusion of innovations.

In practice, a marketing strategy that uses Opinion Leaders should include two steps, recruitment followed by training (Nisbet and Kotcher, 2009). Recruitment could rely on the high social connectedness of potential Opinion Leaders. In the context of energy conservation, candidates would, for instance, be active in or known by local environmental groups. Training would feature involving selected Opinion Leaders in workshops to prepare them to have the greatest possible effect. We would expect their recruitment to require local knowledge.

Place A product can be made accessible at different places and in different ways, which can significantly influence which consumer group is exposed to it the most. Several simulation studies have shown this to be a way to support product diffusion. Variation of placement is commonly operationalized as varying the social group targeted by a marketing campaign (Zhang et al., 2015; Ferro et al., 2010), which we will do in the following as well.

4.3.2. SYNTHESIS: PROPOSED MARKETING STRATEGIES

In this section, we present the marketing strategies that were selected for the simulation 4.1. The respective designs are built on the literature review; this is then followed by using the simulation to assess them.

Table 4.1: Scenarios of marketing strategies to support the diffusion of feedback devices.

Scenario	Targeting	Marketing strategy
GIVE$_{all}$	Any households	Give away free devices
GIVE$_{LL}$	Leading Lifestyles	Give away free devices
GIVE$_{MS}$	Mainstream	Give away free devices
GIVE$_{HD}$	Hedonist	Give away free devices
LEND	Any households	Lending out devices
AWARE$_{all}$	Any households	Raise awareness of device
AWARE$_{LL}$	Leading lifestyles	Raise awareness of device
AWARE$_{MD}$	Mainstream	Raise awareness of device
AWARE$_{HD}$	Hedonists	Raise awareness of device
OL$_{connect}$	Opinion leaders	Connect all peers
OL$_{aware}$	Opinion leaders	Spread awareness to peers of peers
OL$_{ben}$	Opinion leaders	Adopt behavior
OL$_{dev}$	Opinion leaders	Adopt devices

Price We chose the two strategies—giving away and lending out of devices—which reduce the cost of adoption to zero. (1) Giving away a limited number of free devices is a direct way to encourage households to adopt feedback devices. Its rationale is to make the peers of first adopters aware of feedback devices through word of mouth. This has the potential to leverage social influence, which successively entices more peers to adopt devices. (2) Lending out devices enables households to monitor their behavioral performance for a while and potentially change it. After a certain period, the device is returned and lent to another household. The short timeframe of this intervention might increase behavioral relapse, but could–in return–reduce the cost and resource impact of disseminating devices. We considered this strategy, which did not appear in the review, because we took note that a public-private partnership organization[1] has the plan to lend out feedback devices in the future.

Promotion Regarding promotional strategies, we modeled raising awareness of the devices in households to leverage marketing with Opinion Leaders. (1) Raising awareness consists of informing households of the availability of feedback devices.

[1] This is the *'Innovation City Management GmbH'*, which coordinates the roll-out of energy-efficient technology in the city of Bottrop.

Households that have become aware of these devices can from then on choose to adopt them. The resulting adoption of devices can then further spread awareness of devices to the peers of adopters. (2) Opinion Leaders were found in our literature review to have a special role in the diffusion of innovation. We differentiate the assumed training of Opinion Leaders in four ways, which relies on their characteristics of relatively high social participation and levels of innovativeness (Rogers, 2010). (a) Being active communicators, they could mutually connect their respective peers on the topic of feedback devices and heating behavior. Thus, all peers that an Opinion Leader influences would influence each other on this topic. (b) As they communicate actively, they could be encouraged to spread awareness deeper into their social environment. Thus, not just the peers they influence, but also those influenced by these peers could be made aware of a feedback device. (c) Due to their innovativeness, Opinion Leaders could be convinced to adopt shock ventilation, regardless of whether feedback devices continue to be used. In this case, they would exceed social influence on their peers regarding behavior. (d) In the same way, they could be convinced to adopt feedback devices. This could influence their peers towards device adoption.

Place Finally, the two marketing strategies of giving away free devices and raising awareness were cross-combined with variation of place, i.e. the targeting of different consumer groups.

4.3.3. SIMULATING HEATING BEHAVIOR AND FEEDBACK DEVICES

In this section, we will motivate our application of the approach of agent-based modeling and provide the model specifications. This is followed by a description of how a previously published simulation model was adapted and made to capture the selected marketing strategies.

AGENT-BASED MODELING

We used agent-based modeling in order to represent real-world households with computer objects, so-called 'agents.' The relevant decisions and actions of real-world households are captured by decision models and implemented as software algorithms. Relationships between real-world households, e.g. social influence, become links of information flow between these computer objects. Thus, the real-world process of interest is modeled by object-oriented software and can be experimented with in a virtual environment (Sonnessa, 2004).

Agent-based modeling is suited for this study for two reasons. First, the one-to-one relationship (van Dam et al., 2012) between real-world actors and agents makes modeling results, e.g. impacts of modeled policies, more intuitive and therefore more easily understood. Second, agent-based modeling is uniquely able to capture human decision-making (see Briegel et al., 2012; Jager and Janssen, 2012; Sopha et al., 2011), e.g. of innovation adoption and energy consumption behavior (Azar and Menassa, 2015; Chen et al., 2012).

SIMULATION MODEL

In this section are presented the specifications on the used simulation model. A base version of this model was previously presented by Jensen et al. (2016). The model

purpose is to capture the effect of feedback devices on the adoption of energy-efficient heating behavior. For this study, we increased realism of this model by adding a *word-of-mouth* mechanism (see below). The main model elements and their interactions are described in the following.

Household agents Household agents make two relevant decisions: they decide about adoption of feedback devices and of energy-efficient heating behavior. The key processes which the agents undergo include the diffusion of the CO_2 meter; the feedback effect on its adopters, which may create changes in behavior, and the spreading of this behavior change via behavior diffusion. Households within a case area of the 'Innovation City Bottrop'[2] are represented by household agents. They amount to a total of 31,840 agents. These agents are in one of three lifestyle groups, based on commercial marketing data (Sinus Sociovision, 2015) that maps the distribution of sociological lifestyles within the city of Bottrop. Because these lifestyles showed different affinities of adopting sustainable household products (Schwarz and Ernst, 2009), households in the model were accordingly assigned to one of the following lifestyle groups[3]: (1) 'Leading Lifestyles' of higher social status and more modern values, having the highest affinity for adopting feedback devices; (2) 'Mainstream' lifestyles of intermediate social status—including those groups with more traditional values—which have an intermediate affinity for the feedback devices; and (3) 'Hedonist' lifestyles, which have a relatively low social status. The social network that connects the agents has been modeled on two empirical data sources. The way in which this data was applied in generating a social network is presented by Jensen et al. (2016, appx. A).

Technology diffusion The technology diffusion process was transferred from the model by Schwarz & Ernst (2009), which models diffusion of water-saving shower heads. This appliance was used as a proxy technology for feedback devices for the following reasons: (1) both technologies have the purpose of saving thermal energy demand in the household; (2) both technologies can be installed and used virtually without effort; (3) both technologies are cheap, meaning that their purchase does not represent a significant barrier to their adoption or testing.

Following the empirical-based adoption decision model presented by Schwarz & Ernst, agents do not deliberate continuously on adoption, but at a monthly probability (δ_α) of 0.4%. At the point of deliberation, Leading Lifestyles always adopt devices. Mainstream agents adopt devices with a 50% probability and imitate their peers' majority otherwise. Hedonist agents always imitate the majority of their peers.

We extended the previously published version of this model by a word-of-mouth mechanism, to increase model realism. The previous model assumed all households to be be instantly able to adopt feedback devices. Instead, this study assumes that consumers can only adopt devices when *aware* of these devices. They become aware if at least one of their peers has previously been using the device.

[2] www.icruhr.de

[3] Names of lifestyles are used as in the cited sources. Use of this naming in this study is intended as a value-free reference to the Sinus marketing typology.

Feedback effect The way feedback devices affect behavior is modeled based on field tests of the CO_2 meter (Jensen et al., 2016): households that use the CO_2 meter adopted shock ventilation with a probability of ca. 83.3%; this behavior change further saved around 8% of a household's heating energy.

Behavior diffusion Agents were modeled to deliberate on whether or not to adopt shock ventilation at random events. The assumed likelihood of these events over time was based on the search frequency on Google for the German term for shock ventilation (i.e. 'Stoßlüften'). We modeled the likelihood of deliberation on behavior adoption as a sinus curve that was scaled linearly as in Eq. 4.1–4.2 and that peaks during winter.

4

$$\delta_{\beta,annual}(t) = \begin{cases} 0 & \text{before JUN 2008} \\ 0.235 & \text{after JUN 2009, before JUN 2010} \\ 1 & \text{after JUN 2010} \end{cases} \tag{4.1}$$

$$adoption = \begin{cases} 1 & \text{if } \mathrm{SN}_i \geq \mathrm{THLD}_i^* \\ & \\ 0 & \text{else} \end{cases} \tag{4.2}$$

At deliberation, the behavioral intention of individual household agents is determined by a decision model that is based on the Theory of Planned Behavior (Ajzen, 1991). Only if the ratio of influencing peers who adopt the behavior exceeds a threshold, adoption of the behavior take place. Over time, this threshold decreases for all agents, as they are assumed to receive positive information about shock ventilation from the media.

PARAMETERIZATION

The model parameters and their range Table are shown in 4.2. All the simulation results presented here rely on a combination of model parameterizations. These parameters were selected for their ability to present behavior diffusion patterns that represent empirical patterns. For this parameter search, which was based on Pattern-Oriented Modeling (40), we applied three empirical patterns (Jensen et al., 2016): (1) adoption of shock ventilation in the study area would lie in the range of 32.3% to 44.3%; (2) 8% to 23% of adoptions of shock ventilation results result from social influence via personal contact; the rest would come from information from media; (3) the majority of agents who adopt shock ventilation at the beginning of a simulation run would adopt it intentionally.

4.3.4. IMPLEMENTATION OF MARKETING STRATEGIES

The following section discusses how the selected marketing strategies were implemented in the simulation model.

All strategies are comparable in scale of implementation and timeframe. Regarding scale, 1,000 household agents of the virtual city were sampled, representing about 3.1% of the overall population. The only exception to this is the strategy of lending out devices; in this simulation, 1,000 devices were lent out. Implementation of each strategy starts in

Table 4.2: **Parameterization** used in the simulation experiments.

Parameter	Value	Meaning
$p(\beta_{i,t_0} = 1)$	[0.27, 0.39]	Initial SV behavior adoption share
$THLD^*_{mean}$	[0, 1]	Mean of behavior adoption threshold
$THLD^*_{std}$	0.3	Std. of behavior adoption threshold
$\delta_{\beta,event}$	]0, 0.04]	Rate of behavior delib. trigger events
$\Delta_{\beta,ATT}$	]0, 0.006]	Monthly increment to attitude towards SV
$p(\alpha_{i,t_0} = 1)$	0	Initial feedback device adoption share
δ_α	0.004	Technology adoption deliberation rate
$p(\alpha^*)$	0.833	Success rate of feedback devices
t_0	0	Time step (month) of initialization
t_{int}	120	Time step (month) of intervention start
t_{end}	300	Time step (month) of end of simulation
d_{NBHD}	200	Max. length (m) of neighborhood edges
p_{NBHD}	0.5	Ratio of edges within neighborhood

January 2016 and is simulated for 15 years, amounting to 180 monthly intervals in the model.

Price The 'Giving Away Free Devices' scenario was run as follows: (1) 1,000 random households were selected. (2) These were made adopters of feedback devices. (3) The peers influenced by them thus become aware of feedback devices.

Lending out devices was implemented as: (1) 250 households were randomly selected, to whom devices were lent for three months. This was based on the assumption that 1,000 devices were lent out once per year for 3 months. (2) At the point of device adoption, a household has an empirical probability of 0.83 of starting shock ventilation. (3) After device adoption, the household continued to re-evaluate behavior adoption as usual. Consequently, relapsing to earlier behavior patterns was not modeled explicitly, but was possible.

Promotion The 'Raising Awareness' scenario was run by: (1) 1,000 random households were made aware of feedback devices. (2) These households would from then on, with a monthly probability of δ_α, consider the adoption of feedback devices.[4] As defined in the model, if a household adopts a device, the peers influenced by this household would become aware, too.

Strategies based on 'Opinion Leaders' were run as: (1) The 1,000 household agents that influence the most other agents were selected as Opinion Leaders[5]. (2) Depending on the respective scenario, these Opinion Leaders become active in one of four ways. (a) Additional links are created that mutually connect their peers in the social network. (b) They spread awareness of the devices to their peers and to the peers of their peers. (c) They adopt energy-efficient behavior and continue to do so. (d) They adopt feedback devices themselves and raise awareness of these among peers.

[4] Thus, making a household aware of devices does not make it instantly consider device adoption.

[5] Note that 'Opinion Leaders' is not coterminous with 'Leading Lifestyles'. Opinion Leaders appear in all lifestyle groups.

Place Product placement was implemented by differentiating the strategies of ‘Giving Away Devices’ and ‘Raising Awareness’: the randomly selected households were drawn from the respective target lifestyle group; see Table 4.1.

4.4. RESULTS AND DISCUSSION

To answer the stated research question, we conduced four simulation experiments. The first two establish a connection between marketing strategies and their effects, both for the case study of the device under review and for the ‘virtual city’ that was modeled. Experiments 3 and 4 test the generalizability of the findings for this case.

(1) *Reference scenario.* We first simulated ventilation behavior as would be expected without any effect by feedback devices. This serves as a reference scenario from which the effects of marketing can be derived.

(2) *Effects of marketing strategies.* In this experiment, the effects of marketing strategies are analyzed and compared. These effects are separated into device adoption and the behavior change induced by marketing. As a result, it is possible to identify the most effective and cost-efficient marketing strategies and assist in the identification of stakeholders capable of implementing such strategies.

(3) *Sensitivity to policy location.* A central aspect of flexibility in large-scale marketing measures is location, e.g. measures carried out in different locations of a city. We thus compare the effects of the same interventions, but carried out in different neighborhoods of the same city. This experiment thus tests to what degree effects are generalizable regarding the location of implementation in a city.

(4) *Sensitivity to urban structure.* Given that the previous experiments simulate the city of Bottrop as a case study, we test generalizability to other cities. Therefore, we compared the experimental results of the case study of our model city with four other virtual cities with systematically varied socio-spatial structures.

4.4.1. EXPERIMENT 1: REFERENCE SCENARIO OF BEHAVIOR DIFFUSION

In this experiment, we generated a reference scenario of this behavior in the absence of any measures. The simulated marketing strategies will later be compared to this reference scenario in order to identify their impact.

Figure 4.1 presents the reference scenario of behavior diffusion for Bottrop.

Over time, the share of people who adopt shock ventilation practices generally increases, both according to the mean and within the 25^{th} and 75^{th} percentiles. One of the main factors for this trend is the effect of positive information from media in the model. The stepwise increase in the adoption of shock ventilation occurs because energy-efficient ventilation is more relevant to households during winter (Jensen et al., 2016).

Despite this positive trend, future behavior becomes increasingly uncertain over time. Fig. 4.1 shows that over time the gap between the 25^{th} and 75^{th} percentiles, as well as between minimum and maximum, of adopting shock ventilation increases. Nevertheless, the trend towards more adoption of shock ventilation remains. Moreover, most simulation runs lie within a relatively narrow range between the 25^{th} and 75^{th} percentiles.

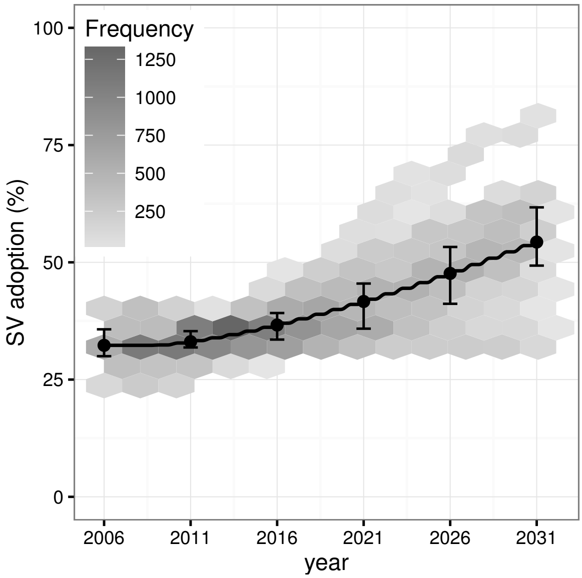

Figure 4.1: **Behavior diffusion in the absence of feedback devices.** The mean share of behavior adoption over all simulation runs is shown by the black line. The 25^{th} and 75^{th} percentiles are shown by the whiskers. In the background, the frequency of projected data points (from 280 simulation runs) is shown by the shading of the gray tiles.

4.4.2. EXPERIMENT 2: SIMULATING MARKETING STRATEGIES

We further compared marketing strategies based on their effect on the level of device diffusion and on the adoption of shock ventilation practices, which is the main endpoint of interest in this study.

MARKETING EFFECTS ON TECHNOLOGY DIFFUSION

We analyzed the effects of marketing strategies on device adoption in two steps: (1) for each strategy we assessed the level of adoption of feedback devices over time; (2) we analyzed in more detail the strategies of greatest impact.

Table 4.3 shows the effects of all simulations of marketing strategies on technology adoption. Adoption rates are shown for 5, 10 and 15 years after policy implementation. In addition, conversion rates express the number of adopting households after 15 years relative to the scale of the marketing strategies.

Simulation results show that marketing strategies varied significantly with regard to impact. Some strategies caused over 10% of households to adopt a feedback device. Conversely, other strategies had no effect at all. Thus, conversion rates ranged from 6.43 to 0; i.e. for each household targeted by a marketing campaign (or device lent out, respectively), up to ca. 6 adopters were gained in 15 years.

Targeted marketing was most effective when addressing the Leading Lifestyles group. This increased effect is based on two facts. (1) Leading Lifestyles were modeled to be most inclined to adopt feedback devices. (2) Leading Lifestyles have more influence on other households than other lifestyle groups do (Jensen et al., 2016, Table A.3).

Table 4.3: **Effect of marketing strategies on technology adoption.** ΔFD describes the effect on the share of adoption after 5, 10 and 15 years. Standard deviations in parentheses. The conversion rate describes how many households adopt the feedback device after 15 years relative to those who were targeted by the respective marketing strategy.

ID	ΔFD after 5 yrs (%)	ΔFD after 10 yrs (%)	ΔFD after 15 yrs (%)	Conversion rate after 15 years
GIVE_{all}	4.5 (0.1)	6.5 (0.2)	9.2 (0.4)	2.93 (0.13)
GIVE_{LL}	5.4 (0.1)	8.2 (0.2)	11.7 (0.3)	3.73 (0.1)
GIVE_{MS}	4.6 (0.1)	6.7 (0.2)	9.4 (0.3)	2.99 (0.1)
GIVE_{HD}	3.5 (0.1)	4.4 (0.2)	5.7 (0.3)	1.81 (0.1)
LEND	0.8 (0)	0.8 (0)	0.8 (0)	0.25 (0)
AWARE_{all}	0.4 (0)	1.1 (0.1)	2 (0.1)	0.64 (0.03)
AWARE_{LL}	0.9 (0.1)	2.3 (0.2)	4.2 (0.2)	1.34 (0.06)
AWARE_{MS}	0.4 (0)	1.1 (0.1)	1.9 (0.2)	0.6 (0.06)
AWARE_{HD}	0 (0)	0 (0)	0 (0)	0 (0)
$\text{OL}_{connect}$	0 (0)	0 (0)	0 (0)	0 (0)
OL_{aware}	4.5 (0.2)	9.5 (0.2)	14.9 (0.3)	4.74 (0.1)
OL_{beh}	0 (0)	0 (0)	0 (0)	0 (0)
OL_{dev}	8.3 (0.2)	14 (0.2)	20.2 (0.3)	6.43 (0.1)

Combined, these two factors create a ‘trickle-down’ effect in the diffusion of feedback devices: an effective spreading from households of higher social status to those of lower status.

The impact of marketing strategies generally increased over time. This is driven by word-of-mouth processes reinforcing the marketing. After device adoption of an agent, its non-adopting peers become aware of the device and thus become capable of adopting devices in the future. The only exception to this mechanism is the marketing strategy of lending out devices to households, for which the word-of-mouth mechanism is not modeled.

Further, marketing strategies that address Opinion Leaders have the greatest conversion rates. This is directly based on their high degree of social engagement. This results in an ability to influence more households than average (Rogers, 2010). Due to the higher likelihood of households of higher social status influencing other households (Jensen et al., 2016), high social engagement is often disproportionally found in the group of Leading Lifestyles.

Following this aggregated comparison, we analyzed the most promising strategies in detail. This aimed to analyze the effect over time as well as in ways that differentiated among lifestyle groups; it also facilitates a more detailed discussion on the most effective marketing strategies. These were the strategies GIVE_{LL}, OL_{dev}, and OL_{aware}. Figure 4.2 shows the diffusion of feedback devices by the lifestyle groups over time.

Among the marketing strategies that were most effective, differentiation among lifestyle groups is consistent. In all cases, device adoption was greatest for Leading Lifestyles, lower for Mainstream, and lowest for Hedonists.

Marketing strategies also show variance in the degree to which they reach the three lifestyle groups. When targeting Leading Lifestyles, the difference in adoption between this group and the other ones increased. The relatively effective strategy of targeting exclusively the Leading Lifestyles group (in scenario GIVE_{LL}) leads to increased disparities in the use of shock ventilation. This suggests a tradeoff between the effectiveness of a strategy and the penetration levels required to reach other lifestyle

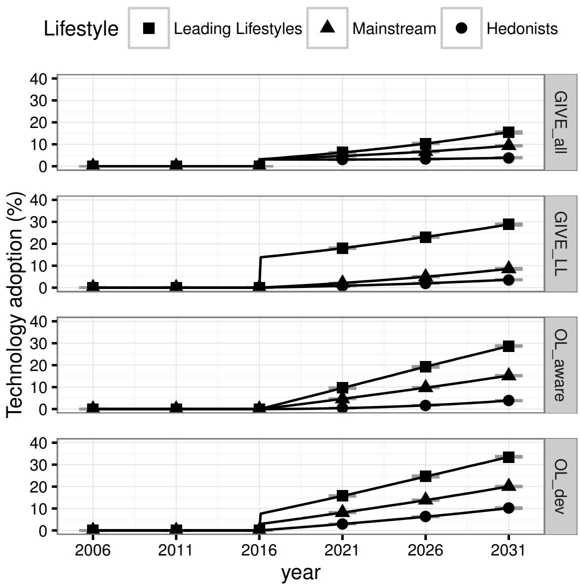

Figure 4.2: **Device adoption in prototypical interventions.** Device adoption in prototypical interventions. It shows adoption levels of feedback devices over time, differentiated by the 'Leading Lifestyles,' 'Mainstream,' and 'Hedonist' lifestyle groups. Marketing strategies start in 2016.

groups: targeting Leading Lifestyles is effective, but leads to more unequal results between lifestyle groups.

MARKETING IMPACT ON BEHAVIOR DIFFUSION

In the following, we analyze the simulated effect of marketing strategies on the adoption of energy-efficient ventilation behavior. As above, Table 4.4 presents the aggregated effects of all strategies.

The greatest impact on behavior change was achieved by using the marketing strategy based on lending out devices–in contrast to the small increase in overall device adoption it created. This is explained by the fact that each device is lent to more than one household agent. We argue this can be seen as a strong effect, in light of the fact that a device is lent out only once per year and that it is–in this strategy–only available through lending.

Targeting Opinion Leaders proved effective for behavior change–particularly when giving feedback devices to them. For instance, this is more effective than (only) convincing them to adopt energy-efficient behavior. This difference is explained by the fact that by giving away devices, the adoption of devices can spread over time, which in turn means they create more adopters of shock ventilation (Jensen et al., 2016).

Just as it was for device adoption, targeting the Leading Lifestyles group with marketing about behavior change was shown to be most efficient. Conversely, targeting was only somewhat effective for Mainstream households and least effective for Hedonists. Once again, the greater impact that results from targeting Leading Lifestyles is explained by their different centrality in the social network. This, however, serves to

Table 4.4: **The effect of marketing strategies on the adoption of shock ventilation practice.** ΔSV describes the effect on the share of those who adopt after 5, 10 and 15 years (the significance of difference to baseline scenario is shown; *: p <0.1; **: p <0.01). The conversion rate describes how many households adopt the feedback device after 15 years relative to how many were targeted by marketing.

ID	ΔSV after 5 yrs (%)	ΔSV after 10 yrs (%)	ΔSV after 15 yrs (%)	Conversion rate after 15 yrs
GIVE$_{all}$	2.9 (9.5)	4.2 (12.9)	5.2 (15.8)	1.66 (5.03)
GIVE$_{LL}$	3.3 (9.3)	**5.2** (12.7) *	**6.5** (15.5) *	**2.07** (4.94)
GIVE$_{MS}$	2.8 (9.5)	4.1 (12.9)	5.2 (15.7)	1.66 (5.00)
GIVE$_{HD}$	2.4 (9.4)	3.2 (13)	3.7 (16.1)	1.18 (5.13)
LEND	**7.9** (9.2) **	**14.5** (11.9) **	**18.9** (13.9) **	**6.02** (4.43)
AWARE$_{all}$	0.3 (9.8)	0.6 (13.5)	0.9 (16.5)	0.29 (5.25)
AWARE$_{LL}$	0.3 (9.7)	1.1 (13.2)	1.8 (16.2)	0.57 (5.16)
AWARE$_{MS}$	0.4 (9.8)	0.8 (13.6)	1.2 (16.6)	0.38 (5.29)
AWARE$_{HD}$	-0.1 (9.9)	-0.1 (13.6)	-0.1 (16.7)	-0.03 (5.32)
OL$_{connect}$	0.4 (10)	0.8 (13.8)	1.2 (17)	0.38 (5.41)
OL$_{aware}$	2.6 (9.5)	**5.5** (12.7) *	**7.8** (15.3) *	**2.48** (4.87)
OL$_{beh}$	3.3 (9.3)	4.1 (12.9)	4.3 (16.2)	1.37 (5.16)
OL$_{dev}$	**5.8** (9.2) *	**9.2** (12.4) **	**11.5** (15) **	**3.66** (4.78)

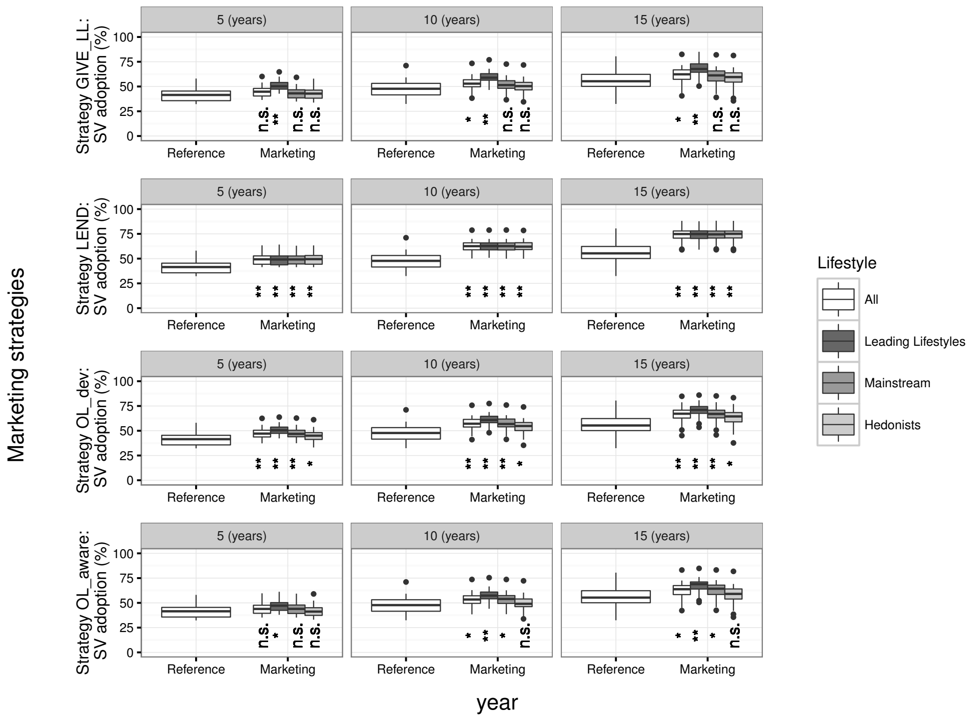

Figure 4.3: **Adoption of shock ventilation in the most effective marketing strategies.** Adoption by marketing is compared to the reference scenario in the absence of feedback devices. Comparison is shown separately for all agents and the three lifestyle groups, respectively.

reinforce marketing campaigns. When raising awareness of devices is the issue, one additional factor is the different level of interest in adoption. After being made aware of such devices, Leading Lifestyles adopt devices eventually, and Mainstream agents to an intermediate degree, but Hedonists only do if the majority of their peers already

do. Thus, the awareness campaigns prompt word-of-mouth effects of different strengths among the different demographic groups.

Marketing strategies that are based on creating awareness of the availability of devices appears to have the lowest rate of effectiveness. In fact, making Hedonist agents 'aware' had no effect at all. This is because even if agents of this group become aware of devices, they would only adopt them if the majority of their peers have already done so.

We analyzed scenarios with the highest effects (i.e. GIVE_{LL}, LEND, OL_{dev}, and OL_{aware}) in detail, see Figure 4.3. Of these strategies, LEND is the only strategy that affected all lifestyles equally. This is because agents are selected randomly for devices being lent to them. Diffusion of technology does not take place. Consequently, the different levels of interest in feedback devices among lifestyle groups do not affect the overall impact of their use.

The other strategies exert the greatest effect on households in the Leading Lifestyles group. Even strategies OL_{beh} and OL_{dev}, which only target Opinion Leaders, had the highest impact on this group. This is highlighted by the significance levels in Fig. 4.3. This difference results because households in this lifestyle group are well-connected socially and relatively interested in the adoption of feedback devices.

Cost efficiency of marketing In this section, after having analyzed the effectiveness of marketing strategies, we discuss cost efficiency. We first estimated the cost of the main components of marketing feedback devices. From this, it is possible to determine the cost efficiency of the modeled marketing strategies in inducing behavior changes.

We argue that the cost of marketing depends on three general components: awareness, devices and training, as indicated in Table 4.5. Awareness represents either making a household aware of feedback devices or facilitating their engagement in other marketing strategies. Its cost is estimated to be €5–20 per household, assuming an online marketing campaign that is geographically confined to one city. On average, it costs less than €2 to create awareness in a customer (i.e. 'cost per click') (Hochman Consultants LLC, 2016). Additionally, designing an awareness campaign would result in estimated costs of €5–20 per household. Device costs would be €50–75, representing the costs of parts and assembly of a CO_2 meter. Training of Opinion Leaders would amount to €20–100 per Opinion Leader, ranging from simply providing catering for two workshops, up to the potential cost of a location and staff for training.

Table 4.5: Cost components of marketing strategies for feedback devices.

Cost component	**Represents**	**Min. cost (€)**	**Max. cost (€)**
awareness	Making one household aware	5	10
device	Giving away one device	50	75
training	Training an Opinion Leader	20	100

Table 4.6 compares marketing strategies in their costs and cost efficiencies. The cost of the different marketing strategies are calculated as follows. The GIVE strategies require making households aware of the availability of devices and then providing them with such devices. For the LEND strategy, the cost of awareness is inversely correlated with the number of times a device is lent out (i.e. once per year over 15 years). The AWARE

strategies naturally only include the costs of making households aware. Leveraging Opinion Leaders (OL strategies) requires raising the awareness of potential Opinion Leaders, and then providing them with training. All strategies are related to either the number of households that are targeted or the number of devices that are lent out, which is the same for all strategies.

We will first identify the most cost-efficient ones within the four groups of marketing strategies, before proceeding to compare these four groups. Within the two categories of 'Raising Awareness about Devices' and 'Giving Away Free Devices,' all strategies are assumed to have similar costs. Thus, the most effective strategies from these categories within each group are also the most cost-efficient ones (i.e. GIVE_{LL} and AWARE_{LL}). For both categories, these are the ones that target Leading Lifestyles. In the group of 'Leveraging Opinion Leaders,' the most cost-efficient strategy is to use Opinion Leaders to spread awareness about feedback devices (OL_{aware}). Giving feedback devices to Opinion Leaders (OL_{dev})–the most effective strategy in this group–would nevertheless also result in higher costs and is therefore less cost-efficient.

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Among these best strategies from these four groups, raising awareness about feedback devices among the Leading Lifestyles group was the most cost-efficient. Lending out feedback devices (LEND) and raising awareness of them through Opinion Leaders (OL_{aware}) had a similar level of cost efficiency. However, the cost efficiency range of the lending strategy is less uncertain and slightly better. Giving out feedback devices to the Leading Lifestyles (GIVE_{LL}) was the least cost-efficient approach.

Stakeholders available for implementation The availability of stakeholders to implement the marketing strategies simulated here is a critical question. Available stakeholder types would first need an interest in households using a feedback device or in heating their homes efficiently. Second, they should be capable of implementing such strategies. The following section discusses what types of agents would be suitable stakeholders; these are presented along the three highlighted marketing strategies regarding price, promotion and place.

(1) Giving discounts on feedback devices or giving them away for free requires significant financial resources. This in turn requires stakeholders to be sufficiently motivated. This seems to be the case for at least two stakeholder types. First, a housing rental company would have substantial advantages in convincing its tenants to practice shock ventilation, which would reduce indoor humidity and mold damage to buildings (Galvin, 2013). Energy utilities—through the energy context of their customer relationships—could market the CO_2 meters to their customers as a tool to save energy as well. These utilities, in many EU countries, are also the main providers of Smart Home devices; feedback devices for heating behavior can be integrated into these systems as well. By giving out devices at lower prices, the utility could benefit from improved customer relations.

Regarding the lending out of feedback devices, public-private partnership organizations, such as the aforementioned *Innovation City Management GmbH* could be a suitable stakeholder to lend out feedback devices. In the past, this company has even declared an interest in doing so.

Table 4.6: Cost-efficiency of scenarios

Marketing strategy	Cost composition	Marketing cost per HH/device (€)	Conversion rate	Behavior conversion cost per HH (€)
GIVE_{all}	$(awareness + device) \cdot nr\_households$	55–85	1.66	33–51
GIVE_{LL}	$(awareness + device) \cdot nr\_households$	55–85	2.07	**27–41**
GIVE_{MS}	$(awareness + device) \cdot nr\_households$	55–85	1.65	33–52
GIVE_{HD}	$(awareness + device) \cdot nr\_households$	55–85	1.17	47–73
LEND	$(awareness \cdot years + device) \cdot nr\_devices$	130–155	6.01	**22–25**
AWARE_{all}	$awareness \cdot nr\_households$	5–10	0.29	17–34
AWARE_{LL}	$awareness \cdot nr\_households$	5–10	0.59	**8–17**
AWARE_{MS}	$awareness \cdot nr\_households$	5–10	0.38	13–26
AWARE_{HD}	$awareness \cdot nr\_households$	5–10	0	∞
$\text{OL}_{connect}$	$(awareness + training) \cdot nr\_households$	25–110	0.39	64–282
OL_{aware}	$(awareness + training) \cdot nr\_households$	25–110	2.48	**10–44**
OL_{beh}	$(awareness + training) \cdot nr\_households$	25–110	1.37	18–80
OL_{dev}	$(awareness + training + device) \cdot nr\_households$	75–185	3.66	20–51

(2) Stakeholders can inform consumers about the availability of feedback devices via advertisement campaigns. For instance, consumer advisory organizations can provide such information to households. Due to the relatively low costs of advertising, all interested stakeholders would in principle be able to provide such information.

We argue that leveraging Opinion Leaders should preferably be carried out by a stakeholder that has high potential of reaching them. We expect Opinion Leaders to be found if they are active in civil society, e.g. in environmental conservation groups. Ideally, such Opinion Leaders would be stakeholders from a cross-section of society rather than a homogeneous connection, e.g. of a housing company or a retail store. Instead, a consumer advisory organization could be better suited to identify Opinion Leaders, due to its local knowledge.

(3) We stress that stakeholders differ significantly in their capabilities to target social groups. Housing companies and energy utilities have direct connections to many households. In the past, charity organizations have also given away energy-saving appliances to these households (Caritas, 2016). This could also be done with feedback devices. In principle, public welfare systems could implement energy savings and split the savings between the beneficiaries and the taxpayers. However, this was found to be unfeasible in Germany for legal reasons (Institut für Energie-und Umweltforschung Heidelberg GmbH, 2009). Retail shops, however, are also interested in the spread of novel technology. They would have the option to advertise and supply novel devices.

Combining this availability of stakeholders to implement marketing strategies with the simulated impacts of these strategies revealed two insights regarding stakeholders that appear relevant for marketing feedback devices.

First, stakeholders whose interest focuses on lower-income groups appear less suited to support the marketing of feedback devices. This is due to the finding that targeting households of high social status makes marketing more effective in general than the targeting of households of lower social status. Consequently, stakeholders focusing on welfare services to low-income households would only be suitable to market feedback devices to a limited degree.

Second, the contrasting impacts of the lending strategy in the adoption of technology and behavior suggest that this strategy is best implemented by stakeholders with an interest in maximizing behavior change, instead of device adoption. Some stakeholders (e.g. retailers) could be more interested in maximizing device adoption rather than any behavioral changes on the part of their customers. Others (e.g. consumer advisory organizations) could be more interested in creating behavior change. For the strategy of lending out devices, the number of adopted devices is low, whereas the impact on behavior change is relatively high. With the relatively low number of devices needed for the lending strategy, this in particular would dovetail with the interests of the latter stakeholder group.

4.4.3. EXPERIMENT 3: GENERALIZABILITY ACCORDING TO NEIGHBORHOOD

Besides knowing which marketing strategies are effective, it would be useful to know *where* their implementation would be most effective. Likewise, if marketing is carried

out at one area, it is of practical interest how other areas are affected by this. Therefore, we compared the impact of marketing between different parts of the city of Bottrop.

As a first step of this comparison, we chose a simulated implementation of one relatively effective marketing strategy, GIVE$_{LL}$, in the case study city in general, as well as in three of its neighborhoods. For all of these three areas, sufficient households of each lifestyle group were available. We chose this strategy because it is the most effective strategy that (unlike the LEND strategy) can facilitate the process of device diffusion–and thus would in principle be most prone to spatially differentiated impacts.

Figure 4.4 shows the location of these three neighborhoods in which the policy is implemented, and adoption of shock ventilation 15 years after strategy implementation for each neighborhood. The results suggest that marketing has the highest impact at its location of implementation. This is shown by the consistent pattern that the neighborhood in which the policy was implemented is also subject to the greatest impact.

The results further indicate that the neighborhood in which the policy was implemented is the only one which diverges significantly in impact from the city in general. Targeting an individual neighborhood with a given policy implementation leads to a different effect from this intervention only in this neighborhood. Thus, the place of policy implementation influences the place of greatest effect. Conversely, neighborhoods adjacent to the neighborhood of implementation did not experience any greater impact than those that were at a greater distance.

To test whether varying the specific location of policy implementation matters for the whole city, we compare impacts from these three scenarios on the city level. Fig. 4.5 shows the adoption of shock ventilation practices for the overall city and for all marketing strategies 15 years after implementation.

This comparison indicates that the location of marketing does not significantly affect the impact on a city scale—with the exception of targeting of Opinion Leaders. The impact caused by the same marketing strategies did not change significantly when implemented at different locations. The only exception to this appeared to be the targeting of Opinion Leaders. This was shown to be more successful at the level of the city as a whole. We traced this back to the fact that Opinion Leaders are 'hubs' in a social network. The larger these hubs—ceteris paribus—the more effective their leverage. Not constraining the marketing campaign spatially (e.g. to a neighborhood) would allow the campaign to reach larger hubs. Consequently, greater impacts could be achieved.

Thus, varying the location of policy implementation has two—seemingly contrasting—effects: concentrating policy implementation in a neighborhood increased its effect locally. Conversely, such concentration of implementation did not significantly change impact on the city scale.

4.4.4. EXPERIMENT 4: GENERALIZABILITY FROM THE CASE CITY

In addition to the sensitivity to the place of marketing, it is also important to know whether findings also hold for cities other than the modeled city in the case study. Testing previous findings from this study would allow a determination of generalizability to other cities. This knowledge is important for any actions derived from this study that will be outside the case of Bottrop.

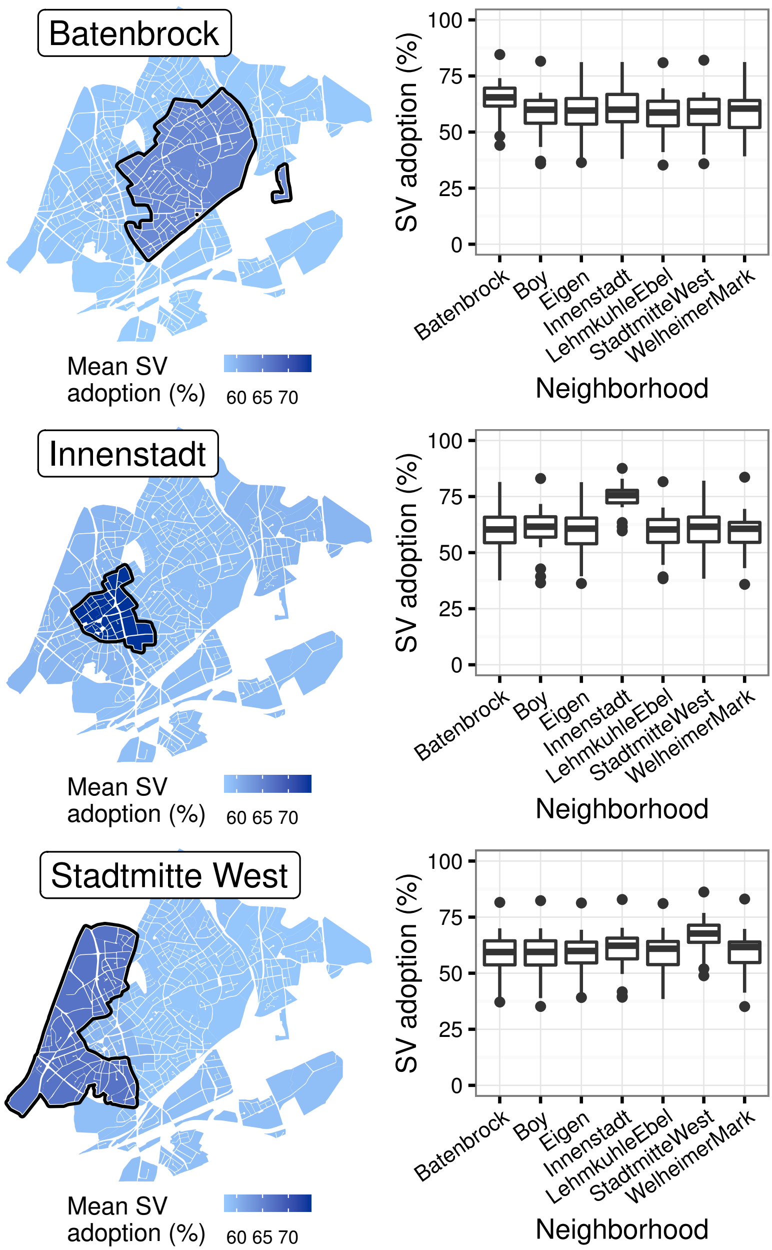

Figure 4.4: **SV adoption in neighborhoods at various locations of intervention.** Maps and box plots show the share of adoption of shock ventilation practices by neighborhood. Marketing strategy 'GIVE$_{LL}$' is implemented in the three neighborhoods 'Batenbrock', 'Innenstadt' and 'Stadtmitte West', shown in this order.

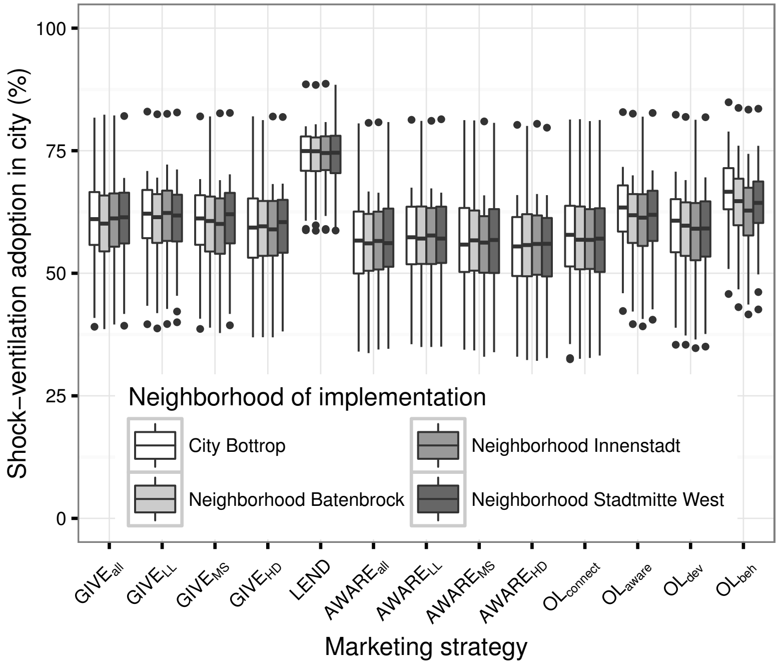

Figure 4.5: **Overall adoption of shock ventilation at various places of marketing.** For each marketing strategy, adoption throughout the entire city was compared 15 years after initial marketing in the whole city or in one of three neighborhoods.

To test this sensitivity, we compare marketing effects among the following five cities:

(1) The model city of Bottrop serves as a reference.

(2) Two cities were generated that, respectively, decrease and increase local clustering of lifestyles. This was implemented by either completely clustering or mixing lifestyles at the street level. As a result, however, the difference in social structure between neighborhoods was only minimally affected. This variable is likely to differ among cities, as other cities would be less or more homogeneous socially.

(3) Two random cities were used to test for extreme variation in urban structure. They were generated by moving the modeled households from the virtual case city to a random location in a spatial bounding box the size of Bottrop. These households were then connected by a newly generated social network that, like for the modeled city, corresponds to the empirical data on social structure. We thus randomized the spatial structure of the virtual city case, without compromising the realism of the social network. This measure did not change the relative composition of lifestyles between the three cities either.

Fig. 4.6 compares adoption of shock ventilation between these five virtual cities for all marketing strategies, 15 years after implementation. These strategies are simulated over all empirically calibrated parameter combinations.

Results show that the difference in impact among cities of an intervention appears insignificant. The differences in implementation strategies is a stronger factor than the

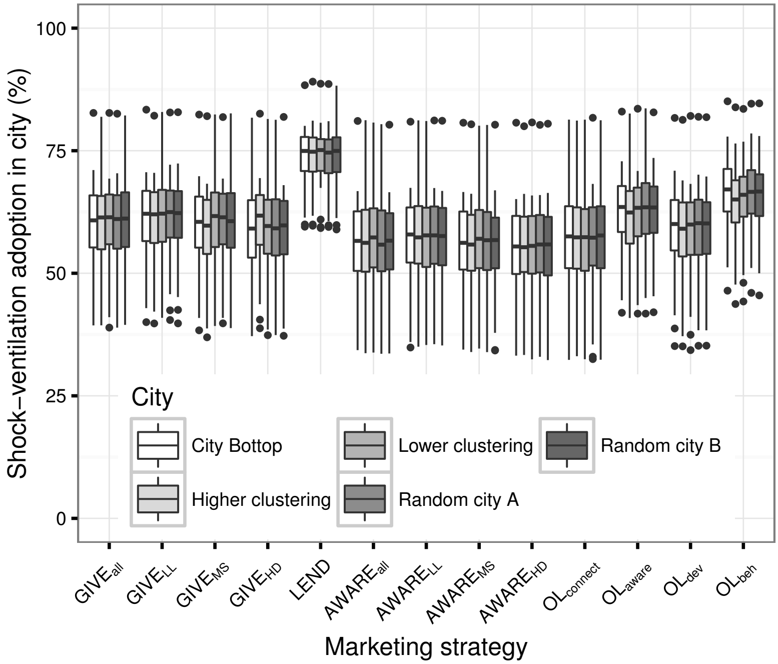

Figure 4.6: **Adoption of shock ventilation practice at various virtual cities.** For each marketing strategy, adoption throughout an entire city was compared 15 years after carrying out marketing strategies in one of five virtual cities.

differences among cities. The degree of local clustering of lifestyles and socio-spatial structure do not appear to influence the success of a marketing strategy. This could be due to the high ratio of social connections between neighborhoods (50%, see Table 4.2).

However, from the second experiment (see 4.4.2) the conclusion can be drawn that the lifestyle composition in a city would influence the impact of marketing. A city with a higher ratio of households of the Leading Lifestyles group (i.e. of highest social status) would also likely experience greater effects.

Overall, the generalizability of marketing strategies between different cities and urban structures was found to be high. This indicates that policy assessment in this study can be transferred from the model city case to others with a similar composition of lifestyle demographics.

4.4.5. VALIDATION AND LIMITATIONS

For the applied model needed to be assured that simulation results capture the real world, thus *ecological validity* needed to be shown. This was taken out in three ways: (1) Empirical data was directly integrated into the model. This was done for modeling the effect of the CO_2 meter in households, as well as for the probability of feedback actually changing household behavior. (2) We further used 'Pattern-Oriented Modeling,' a validation method that ensures that simulation results coincide with empirically observed patterns (Grimm et al., 2005). In particular, the behavior diffusion process

was validated with this technique. To do this, we used patterns of adoption levels of energy-efficient ventilation behavior, the role of social influence in causing its adoption, and the degree to which this adoption conforms to intentions (see Section 4.3.3). (3) To validate the technology diffusion process, the so-called 'TAPAS validation' method was applied (Frenken, 2006, p. 151).We used an existing model on the diffusion of a relatively similar, environmentally friendly household product class: water-saving appliances (Schwarz and Ernst, 2009). This model was validated with historical diffusion data for this proxy technology. We thus based the diffusion of feedback devices by the diffusion of this proxy, in order to reduce uncertainty about the diffusion of behavior-changing feedback devices.

Limitations We expect the results of this study to be affected by the selected marketing strategies, limitations regarding estimates of marketing costs, and the uncertain nature of forecasting itself.

Some marketing strategies were not possible to be modeled due to the model structure. Moreover, charting the changing preferences of consumers was not possible, because these are not part of the model used. However, we regard the selection of the modeled marketing strategies as appropriate and meaningful. This is because this selection spans a wide range of marketing options and covers its relevant categories of price, promotion, and place. Furthermore, within this selection, we particularly compared strategies that showed as promising in the literature.

Even though we could estimate the cost efficiency of multiple marketing strategies assessed in this study, cost efficiency remained uncertain. Therefore, we limited ourselves to giving cost ranges for the marketing strategies. Consequently, ranges of estimated cost efficiency overlap, making it uncertain which strategies are most cost efficient. However, we regard this uncertainty as inherent, as different stakeholders might have different costs for respective types of marketing. We further dealt with this uncertainty by examining it in the discussion.

Overall, residual uncertainty of the model results has to be considered as high, which naturally calls for a careful interpretation of simulation results. The main reason for this is the discussed high uncertainty of the future of complex socio-technical systems (van Dam et al., 2012). Another reasons is the simplification from reality, which is necessary to any model-based analysis. Finally, also the possibility of partial imprecision of the simulation model could only be excluded to the degree this was done in the validation procedure (see Section 4.4.5). Due to thus residual uncertainty, we consider the most valuable results generated by this simulation study the relatively robust *comparison between* marketing strategies—not necessarily the simulated *absolute levels* of impacts.

4.5. CONCLUSION

In this study we aimed to answer the following research question: *Which innovation management is most effective at creating additional energy-efficient heating behavior via the marketing of behavior-changing feedback devices?* Marketing strategies for feedback devices successfully resulted in additional adoption of energy-efficient ventilation behavior, particularly when: (1) the use of feedback devices was incentivized

economically by giving away or lending out some devices for free; (2) the social influence of well-connected Opinion Leaders (i.e. households that are particularly influential for others) was leveraged to promote the devices; and (3) households of higher social status were targeted primarily by marketing.

The core mechanism creating this effect is the result of two processes: the direct impact of a given marketing strategy and its amplification through the distribution of feedback devices on the one hand, and on the other hand an increase in energy-efficient behavior via social connections. Marketing strategies (e.g. giving away free devices or raising awareness about them among households) can have an effect on their own. These interventions may persuade more households to adopt these devices, which will in turn cause a majority of these device adopters to adopt energy-efficient behavior. This added energy-efficient behavior (being the direct result of the marketing strategy or of device adoption) then amplifies the spread of energy-efficient behavior. Marketing strategies assessed in this study varied significantly in effectiveness and cost efficiency. These differences are summarized in Table 4.7.

Table 4.7: Results on marketing strategies, indicating effectiveness and cost efficiency in creating adoption of energy-efficient heating behavior.

Scenario	**Effectiveness**	**Cost efficiency**
GIVE$_{all}$	+	+
GIVE$_{LL}$	**++**	**++**
GIVE$_{MS}$	+	+
GIVE$_{HD}$	+	+
LEND	**+++**	**++**
AWARE$_{all}$	+/-	++
AWARE$_{LL}$	**+/-**	**+++**
AWARE$_{MD}$	+/-	++
AWARE$_{HD}$	+/-	-
OL$_{connect}$	+/-	-
OL$_{aware}$	++	**++**
OL$_{ben}$	++	+
OL$_{dev}$	**++**	++

Effectiveness of innovation management via marketing This simulation study allowed us to compare the effectiveness of marketing strategies that used economic incentives, promotion, and placement to different degrees.

The economic incentive of lending out feedback devices was the most effective strategy. This approach resulted in the highest ratio of additional adopters of energy-efficient behavior relative to the number of devices that were lent out. The alternative economic incentive of giving away devices for free was successful to a lesser degree. We thus stress the practical potential of lending out individual feedback devices to households.

The promotional approach of raising awareness about the availability of feedback devices was the least effective marketing strategy. The only exception to this was the potential to use Opinion Leaders to raise awareness about the devices not just among their peers, but also among the peers of these peers. In contrast, marketing strategies that caused the greatest impact were those that either gave away devices to households

or targeted Opinion Leaders. In particular, giving devices away to households of the Leading Lifestyles group was effective in convincing more households to start using the devices.

Targeting different social groups with marketing campaigns changed their effectiveness significantly. Targeting Opinion Leaders and members of the Leading Lifestyle group appeared most effective. The effect was greatest for Leading Lifestyles, lower for Mainstream, and lowest for Hedonists. Findings regarding this order of effect were robust in all variants of marketing strategies.[6] Therefore, we suggest primarily targeting Opinion Leaders or households of the Leading Lifestyles. In practice, identification of households to be targeted can be done by using commercial marketing, such as the here applied Sinus marketing typology.

Adjusting the targeting of marketing spatially—within an entire city or its neighborhoods—generally determined the main area of impact, but not the overall impact. Thus, when it is of interest to maximize impact in a local area, then this area should be the focus of marketing activities. For maximizing the impact on a city scale, however, it did not matter which of its parts were targeted. The only exception to the latter finding is the targeting of Opinion Leaders. When targeting these, results indicated the desirability of utilizing the most influential Opinion Leaders from an entire city–instead of being spatially restricted to a single neighborhood.

Overall, we found lending out devices to be the most effective marketing strategy to promote feedback devices. Giving away devices and targeting Opinion Leaders were, regarding device adoption, among the most effective strategies. Raising awareness about feedback devices appeared to be least effective.

Cost-efficiency of innovation management The estimated cost efficiency of marketing strategies has a somewhat different order than their effectiveness. (1) The most cost-effective measure is raising awareness among agents. This strategy, when targeting households of higher social status, is among the least effective, but it is cost effective due to its low price. (2) Lending out feedback devices was the second-best strategy. Even though feedback devices need to be provided for this intervention, their cost is low because a device can be lent out multiple times. (3) Leveraging Opinion Leaders was shown to be slightly less cost-effective than lending out devices, due to the costly training that would have to be given to Opinion Leaders. Nevertheless, the best marketing strategy leveraging the high social engagement and influence of Opinion Leaders was that of raising awareness about feedback devices within their social circle. This strategy combined high effectiveness with a relatively low cost, because no devices need to be subsidized. (4) Finally, the relatively effective marketing strategy of giving away some free devices was found to be least cost efficient, because they require sponsorship of free feedback devices. Of this subset of strategies, targeting households of higher social status still has the best cost efficiency.

We stress that the cost efficiency of these strategies can vary depending on which stakeholder implements them. For instance, if a sponsorship of free feedback devices cannot be done cost efficiently, the marketing strategies of giving away or lending

[6] The only exception is the—relatively successful—strategy of lending out devices, which did not create an effect that varied between lifestyles.

out devices would in turn result in higher costs. Conversely, the cost efficiency of marketing that leverages Opinion Leaders depends significantly on whether training can be supported by available resources or needs to be outsourced (e.g. workshop rooms or training staff).

Role of stakeholders in rolling out feedback devices Stakeholders who might support feedback devices might nevertheless also have very different interests: maximizing device adoption does not necessarily imply the adoption of energy-efficient heating behavior, or vice versa. We have identified some relevant types of stakeholders who likely would be more interested in maximizing device utilization to be, for instance, energy utilities and retailers. Conversely, organizations that might prioritize the end of behavior change could be consumer advisory organizations and public-private partnerships with sustainability goals.

Both these groups could reach their goals with a set of overlapping strategies–with the lending out of devices being the only exception. Both the adoption of feedback devices and of energy-efficient behavior can be supported effectively by leveraging Opinion Leaders and by giving away free devices to initial adopters–preferably those of relatively high social status (i.e. Leading Lifestyles). The only exception is the marketing strategy of lending out, which increased energy-efficient behavior most effectively in our assessment.

Generalizability We tested the generalizability of these findings, comparing the effects from marketing campaigns in a virtual version of Bottrop (as our case-study city) with two other, randomly generated, virtual cities. We determine that the results of this study seem to be generalizable to other cities, including those with very different socio-spatial structures. This has two major implications for our study: (1) marketing strategies that were shown to be successful in the 'virtual Bottrop' would likely also be successful in another city with a similar composition of lifestyle groups; (2) commercial high-resolution marketing data on the locations of consumer lifestyles in a city might not be needed for studies like this. The overall population share of lifestyle groups would suffice instead.

Impact on heating energy demand Campaigns simulated in this study increased the adoption of shock ventilation by up to ca. 18% (σ = 13.9%) after 15 years. This impact was found statistically significant. Given the empirically estimated 8% of energy savings from this ventilation behavior, this would translate into a decrease in energy demand by ca. 1.5% (σ = 1.1%). Similarly to additional shock ventilation, these energy savings would be distributed heterogeneously. Households of higher social status would likely decrease their energy demand more, whereas households of lower social status would less so.

This reveals that, given the low costs of feedback devices, their impact can be relevant on a city scale, but is also limited. Particularly, the overall impact on a broader scale stays below its impacts on individual adopters. Therefore, we suggest that interventions that use the CO_2 meter should be combined with energy-related renovation measures, e.g. replacing building insulation. This is particularly useful as insulating buildings

increases the relative share of ventilation in heating demand; this makes the CO_2 meter particularly useful for well-insulated buildings.

4.6. FUTURE RESEARCH

We see the following opportunities on how future research can add to the contributions of this study.

We suggest to increase robustness of forecasting by refining the applied simulation model in two aspects. First, modeling the decision of adopting feedback devices could be done in more detail. More detailed insight into the process of decision-making would for instance allow the assessment of marketing strategies in more detail, e.g. regarding detailed communication with consumers. Such increased detail would require extensive empirical data on past device diffusion, as well as more specific assumptions on future developments in the energy sector (e.g. regarding energy prices). Second, the here presented method of assessing marketing strategies should be transferred to more cases of feedback devices. This would be advantageous, because it would differentiate the undertaken comparison between marketing strategies.

This study analyzed how feedback devices can be used to conserve heating energy. However, this approach could be compared more closely in its combination with alternative approaches. In particular, the aforementioned alternative of energy renovation could be included, motivated by the interactions between refurbishment and user behavior (Berkhout et al., 2000). From this, we would expect an assessment that included and compared both energy-related renovation efforts and feedback devices to be fruitful and informing for policymakers and stakeholders alike.

We regard the assessment approach of this study to be well-suited for future applications on the diffusion of technology and behavior. We expect to see more cases of simulation assisting the support of behavior changing technology, in order to trigger behavior change towards sustainability on a larger societal scale.

5

AUTOMATING MODEL DEVELOPMENT AND APPLICATION

The best work is not what is most difficult for you; it is what you do best.

Jean-Paul Sartre

5.1. INTRODUCTION

Understanding the prospects of innovations and how they spread is powerful. Mechanistic understanding of the diffusion of an innovation can help explaining their success. For instance, the Theory of Diffusion of Innovations by Rogers (2003) allows understanding diffusions based on general mechanisms of interpersonal interactions. From these, it is possible to infer general patterns and key actors of innovation diffusion. Further, the explanatory power of the general mechanisms of innovation diffusion has been confirmed in empirical cases of diffusing innovations (Schwarz and Ernst, 2009; Sopha et al., 2013; Jensen et al., 2016).

Beyond understanding, found mechanisms can be used for guiding practical actions. Persons and organizations often want to know *"how to speed up the rate of diffusion of an innovation"* (Rogers, 2003). Actions that achieve this can directly be derived from causal mechanisms of the spreading of an innovation. Further, simulation can be used to project and estimate the impact of practical actions. This allows forecasting the impact of these actions from the underlying mechanisms. This study will focus in particular on simulating innovation diffusion with agent-based modeling (ABM). This approach represents real-world actors with computer agents, whose actions towards innovations are modeled by explicit decision models (Delre et al., 2007; Jensen and Chappin, 2016).

However, mechanistic understanding is particularly challenging to gain. It is harder to achieve than statistical inference, which reveals co-occurrence of events in a set of observations. Requirements for gaining it also exceed sole causal understanding, which

At the time of writing, this chapter is in press at the Journal of Environmental Modeling and Software.

'only' requires knowing that one event generally causes another one (Aalen and Frigessi, 2007). Instead, mechanistic understanding implies to know if one event (likely) *"leads to a specific, deterministic behavior in another"* (Leek and Peng, 2015).

ABM can illuminate mechanisms of the diffusion of innovations, but is challenged by time and labor intensive model building (van Dam et al., 2012). Via simulation, ABM links micro-level actions of actors to 'emergent dynamics', e.g. innovation diffusion (Chappin and Dijkema, 2015). Thereby, macro-dynamics of innovation diffusion are 'decoded' by being explained by micro behavior of agents (Grimm et al., 2005; Stern, 2016). Unfortunately, ABM is commonly more time-intensive than its alternatives (e.g. system dynamics (Watts and Gilbert, 2014) and statistical analysis). This limits its practical applicability. In line with these challenges, Garcia and Jager (2011) emphasize the current *"challenge is designing (agent-based models) that are useful (to) managers without programming skills."*

We propose to enable agent-based modeling to overcome these limitations by automated model generation. Several approaches to automation exist, which we propose to combine: (1) Translating simple specifications into executable models. Examples are `http://m.modelling4all.org` and the MAIA framework by Ghorbani et al. (2013), which automatically generate simulation models from specifications by domain-experts. (2) Model building from existing components. A method to this idea is 'TAPAS'[1], via which previously validated models are reused at new applications (Frenken, 2006). (3) Using data for model-building in a structured way. Grimm et al. (2005) proposed 'Pattern-oriented Modeling' to falsify model variants that fail to reproduce a set of patterns from empirical data. This replaces ad-hoc decisions and informed guesses about adequate model structures and parameters with rigid testing against empirical data.

Therefore, the target of this study is to present a process that systematically builds ABMs via the following steps: (1) extracting driving mechanisms from empirical observations on innovation diffusion; (2) projecting diffusions into the future; and (3) assessing the effects of real-world actions and policies ex-ante, via simulation. This study aims to answer the following question: *"Can automated generation of agent-based models on the diffusion of innovation be achieved, and how could this be useful?"* This question will be addressed by specifying an automated software procedure for this task. To further provide *proof of concept*, application of an implementation of this procedure to the diffusion of sustainable products among households will be presented.

The remainder of this study is structured as follows. First, we provide background on agent-based modeling of the diffusion of innovations. Second, the procedure that automates the building of such models is presented. Finally, this procedure is applied to a case of innovation diffusion.

5.2. AGENT-BASED MODELING OF INNOVATION DIFFUSION

This section will provide details on agent-based modeling of innovation diffusion, which is the application domain of the proposed automation procedure. We will show

[1] 'TAPAS' abbreviates *"Take A Previous model and Add Something"*.

that there exists a high degree of standardization of existing diffusion models. This standardization helps automated modeling.

According to Geels and Johnson (2015), there exist four general types of dynamic innovation diffusion models. We hereby focus on innovation models that are dynamic, because innovation itself is a process of change (Kiesling et al., 2012). (1) *Adoption models* capture spreading of an innovation among potential adopters, e.g. how the user base of a new product increases via word-of-mouth. (2) *Models of up-scaling and system building* describe a small system expanding to a larger one, e.g. an electricity system expanding from a decentralized ones to a single centralized system. (3) *Replication and circulation models* emphasize the replication of an adoption during its circulation to other location. Considering replication emphasizes adapting an innovation to other local conditions. (4) *Societal embedding models* consider the embedding of an innovation in business, societal, policy, and user environments.

'Adoption' type models are of special interest to this study. This is because their modeling of *"independent adopters making (adoption) decisions"* (Geels and Johnson, 2015, p. 12) fits well with the actor-centric perspective of agent-based modeling. Adoption type models are represented by 'aggregated' and 'individual level' models (Kiesling et al., 2012). Aggregated models directly model the overall adoption dynamics of an entire population. This approach is represented by the 'Bass model' and commonly modeled with system dynamics (Kiesling et al., 2012). Conversely, 'individual level' models capture the adoption decisions of individuals in a population, from which overall adoption dynamics 'emerge'.

In this study, we will focus on the individual level models, because of their capability to incorporate more aspects of reality. According to Kiesling et al. (2012), 'individual level' models are superior to 'aggregated' ones (such as system dynamics). (1) *Explanatory power* is greater for 'individual level' models, because they explicitly connect behavior and decisions of agents with aggregated diffusion dynamics. (2) *Population heterogeneity* can be captured more detailed in 'individual level' models. (3) *Social processes* (e.g. interactions between consumers) are modeled explicitly. This process can have great impact on diffusion success (Delre et al., 2007). Agent-based 'individual level' models are particularly suited to model social interactions. In contrast to discrete-event simulation, they are capable of modeling detailed social interaction topologies in a computationally efficient way (Watts and Gilbert, 2014). Consequently, this study will focus on innovation diffusion models that are agent-based.

Automating the building of agent-based innovation diffusion models is facilitated by their similar structure. A review by Kiesling et al. (2012) finds that most 'individual level' diffusion models have such a common structure. Accordingly, virtually all agent-based innovation diffusion models are variations of one *meta-model*, shown in Fig. 5.1. This meta-model comprises the following elements: (1) Consumer agents represent the entities than can adopt an innovation. These can be individual persons, households, or groups of households. (2) Social structure is the heterogeneity of consumer agents, e.g. dividing them in different consumer groups. (3) Decision making processes (formalized as *decision models*) are the key actions of consumer agents to model the adoption of an innovation. (4) Social influence between agents (from peers, social groups or overall population) can affect decision making of consumers and is commonly modeled as a

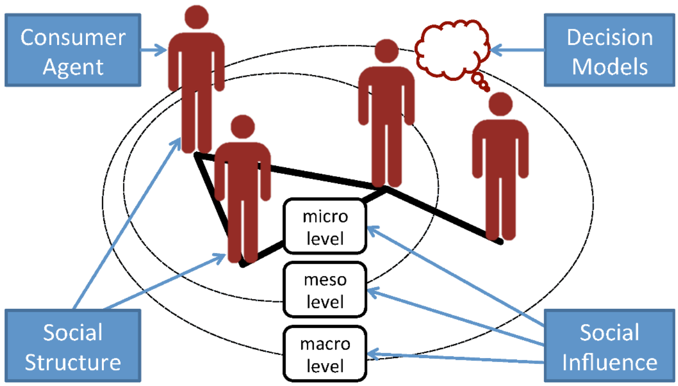

Figure 5.1: **Meta-model of agent-based models of innovation diffusion.** Based on review by Kiesling et al. (2012, Fig. 3).

social network graph. This overall similarity simplifies automated model generation. This is because there is less variation in input data and less structural variation than needs to be considered.

5.3. METHODS

In this section, we will present in detail the automation procedure to building agent-based models on innovation diffusion. We regard this approach as innovative, because it meets a previously unmet demand and was apparently not met this was previously. According to Garcia and Jager (2011), a *"versatile method of easily testing managerial strategies that influence the degree and speed of diffusion processes is not currently available."* When querying the Scopus database for *'agent-based AND innovation AND automat*'*, no existing similar approach was found.

The automation procedure will be presented by describing it conceptually and by giving details on its implementation.[2] Thereafter, proof of concept is given with an application case.

5.3.1. AUTOMATION PROCEDURE CONCEPT

We coin a method as specified in Fig. 5.2, comprising the three phases *preprocessing, inverse modeling,* and *policy simulation.*

Preprocessing This phase is coined *preprocessing,* because input by the user is not given as raw data, but has to be preprocessed. The following types of input data are strictly required for the presented method to execute:

(1) Input data is provided on agents (i.e. the decision-making entities in an agent-based model). For each agent, its location and social group are defined. This attribute of a social group enables us to capture the heterogeneity of agents. Social

[2]Source code of the prototype implementation can be accessed at https://github.com/ThorbenJensen/automated-model-generation

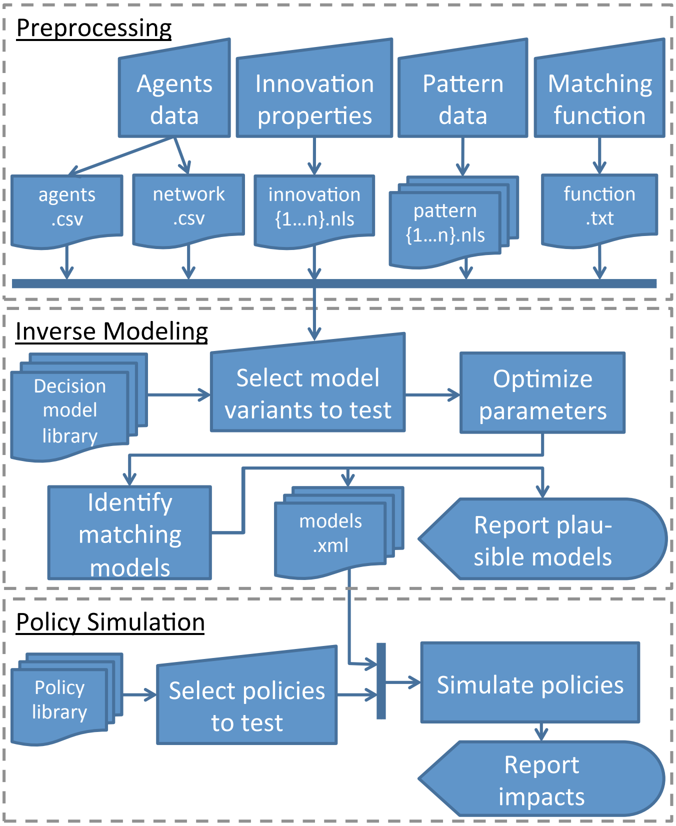

Figure 5.2: **Overview of phases of automation procedure**. The procedure is sub-divided into the subsequent phases *preprocessing* of input data, *inverse modeling* of potentially explaining models, and *policy modeling* of models that were accepted based on the previous phase.

5

influence is defined by a social network graph. For generating a social network graph, we used the algorithm described by Jensen et al. (Jensen et al., 2016, Appendix A.2).

Agents have to be defined by a CSV file with the columns ID, X and Y coordinates, and name of the social group they may belong to. The network graph is provided as a CSV file with the columns FROM and TO, defining directed links between two agents identified by their IDs. For instance, bidirectional influence between two agents would require two lines in this file.

(2) Innovation properties are provided that represent how an innovation is perceived by households. This idea follows Rogers (2003), according to whom diffusion success of innovations depends on generalizable properties. Examples of the innovation properties are relative compatibility, complexity, and trialability.

Innovation properties each have to be provided as NetLogo source files. Each file contains a NetLogo method that sets innovation properties of an innovation as global variables.

(3) Patterns are provided that characterize the dynamics of the real-world process that shall be modeled. These patterns are *"indicators of essential underlying processes and structures"* (Grimm et al., 2005). Each additional pattern reduces uncertainty about which mechanisms could explain the diffusion of an innovation. An example for a relevant pattern is the exponentially increasing adoption share of a successful innovation during its initial diffusion (Rogers, 2003).

Patterns are formalized by provided as NetLogo functions that calculate how well a simulation run matches each pattern. The values returned from these functions represent how well a simulation run suffices a pattern. A returned value of 0 signals a perfect fit with a pattern. With greater divergence from the pattern, this returned value increases. At simulation runtime, these functions query simulation runs and return fitness values for the following matching function.

(4) A 'matching function' describes the desired behavior of an accepted simulation model in terms of the provided patterns. This function weights and combines patterns to describe model output that would be considered realistic. This function assists in finding simulation runs that represent the empirical patterns best.

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The matching function has to be defined by a character string. Variables of this function are the names of the provided empirical patterns (and the functions that calculate matching with these patterns). For an example, see Eq. 5.2 at the application case below.

Inverse modeling The inverse modeling phase identifies models that satisfy the provided matching function.

Within a range of plausibility, pre-defined models are varied in their structure and parameter values. For this, the NetLogo tool *BehaviorSearch* was used (Stonedahl and Wilensky, 2016). It repeatedly runs each potential model, thereby varying its structure and parameters, searching for an optimal fit with the pattern. The optimum that this search converges to is defined by the user-provided matching function. For the application case, we executed BehaviorSearch with a *simulated annealing* optimization (see Table 5.1 for search settings).

At the end of this phase, the user has to choose which tested models from the model library with which structural variation shall be accepted. Accepted model variants should be those that generate realistic results. This decision can be based on the best fitness values and respective parameters, which are reported for each structural variation of each tested model. If a model reproduced all provided empirical patterns, then it can be considered a potential explanation of these input data. Because the user has pre-defined this ideal behavior via the matching function, the fitness value is a strong indicator for this judgement. If model variants of multiple complexity levels match the patterns well, the simplest ones of these variants should be preferred. This serves to manage the risk of 'overfitting' at high structural complexity (Provost and Fawcett, 2013). If required, the reported parameters settings for the best fit of each model variation allow the user to simulate and assess these model settings more closely in NetLogo.

Policy simulation The proposed automation procedure provides the useful function of semi-automatically assessing policies. Here, policies are those actions that aim at

Table 5.1: **Search setting of simulated annealing optimization.** Applied search tool was the NetLogo extension BehaviorSearch. Search parameters are names as in this tool.

Search parameter	Value
Mutation rate	0.05
Temperature change factor	0.95
Initial temperature	1.0
Restart after stall count	0
Evaluation limit	300
Optimization goal	'Minimize Fitness'
Collected measure	'MEDIAN_ACROSS_STEPS'
Fixed sampling	5
Combine replicates	'MEDIAN'

systematically supporting the diffusion of an innovation. Polices are provided in a policy library, which can be extended by the user. Such automated policy modeling is useful, first, because it frees the user from redundant, manual work. Further, running the same set of policies across all models that are accepted by the user based on the inverse modeling results increases robustness of the policy assessment. This can for instance be achieved by averaging over all these forecasts.

Policies are pre-implemented as NetLogo functions and stored as individual NetLogo source files. Users have to choose from a set of policies that support innovation diffusion or define other policy options. The user is recommended to test those policies for all diffusion models that resulted in a sufficient fit with the provided empirical patterns. Each policy simulation is executed from an XML file with the 'BehaviorSpace' tool in NetLogo. These files are derived from a template, but parsed based on the user choices on policies and models, and the respective parameterizations that previously resulted in a best match with the empirical data.

5.3.2. APPLICATION CASE: DIFFUSION OF WATER-SAVING APPLIANCES

We applied the here presented automation procedure to the diffusion of water-saving showerheads. This was motivated by available empirical data of high quality for this case. We used the proposed automation procedure to generate models that explain these data and to test policies. This served as a proof of concept and illustrates the proposed automation procedure. Also, it informs us about the mechanisms with which water-saving showerheads could spread. Policy simulation shows how this spreading could be effectively influenced.

EMPIRICAL DATA FOR APPLICATION CASE

Empirical data on the diffusion of water-saving showerheads was used, as presented by Schwarz (2007).

(1) *Agents data.* Previous research found a significant relationship between lifestyle group and adoption behavior regarding water-saving appliances (Schwarz, 2007). Accordingly, three consumer groups could be clustered: 'Leading Lifestyles', which are of higher social status, are most interested in the adoption of such appliances; 'Mainstream and Traditional' households show intermediate interest in them; and 'Hedonists' are least interested in water-saving appliances.

(2) *Innovation properties.* Properties of water-saving showerheads and conventional showerheads were surveyed. For each lifestyle group, the relative importance of these properties was also surveyed. This allows modeling the choice of consumers regarding the adoption of water-saving showerheads.

(3) *Diffusion patterns.* Two empirical patterns on the diffusion of water-saving showerheads emerged. First, marketing shares in Germany after 15 years of product diffusion show difference in adoption between these consumer groups. Second, the adoption diffusion curve during the first 15 years of innovation diffusion has an exponential shape.

EXISTING MODEL ON SHOWERHEADS DIFFUSION

An agent-based simulation model was previously built based on some of this empirical data (Schwarz, 2007). We will here coin it the 'Schwarz' model. This model describes the decision making of agents regarding the adoption of feedback devices. According to the model, initially no household uses water-saving shower heads. At a monthly deliberation probability of 0.004, each household decides whether to adopt the water-saving option. There is a probability at which agents adopt the technology option that is adopted by the majority of their peers. This probability is differentiated by the three lifestyle groups (Jensen et al., 2015): (1) Leading Lifestyles always adopt the device, regardless of their peers; (2) Mainstream agents adopt devices in 50% of the cases, and imitate their peers otherwise; and (3) Hedonists always imitate the majority of their peers.

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EVALUATED AGENT-BASED MODELS

We created a generic model library of two further models. We coined these models *'Schwarz flexible'* and *'TPB'*, which abbreviates Theory of Planned Behavior.

'Schwarz flexible' model This model is structurally similar to the 'Schwarz' model, but its parameterization was made 'flexible' in two ways. First, the monthly deliberation probability became a flexible parameter between 0.004 and 0.04. Second, the probability of agents to adopt according to the majority of their peers also became a flexible parameter (between 0 and 1) for each social group.

'Theory of Planned Behavior' model The second decision model is based on the *Theory of Planned Behavior* (TPB) by Ajzen (1991). Modeled adoption is based on three factors: the *attitude* towards an innovation (ATT), the *perceived behavioral control* (PBC) over adopting it, and the *subjective norm* (SN) towards adoption from the social environment. For water-saving showerheads, this means that adoption is more likely if first, attitude towards this product is more positive, second, if the adoption is perceived as easy and feasible, and third, if adoption is more common among peers. We used the formalization shown in Eq. 5.1 (Schwarz, 2007).

$$\text{adoption\_intention}_i = (1 - s) \cdot (\text{ATT}_i + \text{PBC}_i) + s \cdot \text{SN}_i \tag{5.1}$$

According to this model, an agent calculates utility for each option i and adopts the one with the highest adoption intention, based on the following factors. 'ATT_i' is the product of two vectors: properties of innovation i and weights (i.e. importance)

that the agent's social group assigns to these characteristics. An example of such a characteristic is environmental-friendliness of an innovation. 'PBC_i' is a product of innovation characteristics (that translate into the ease of adoption) and the respective weights of importance for the social group. An example is the purchasing cost. 'SN_i' is the ratio of peers of a household that use product *'i'*. The parameter *'s'* is the importance to practice the same behavior as its peers, motivated by a need for social cohesion or uncertainty about the product.

We differentiated these two models by an optional word-of-mouth (WOM) mechanism. Without this mechanism being active, all agents can principally deliberate on adoption at any time. If this mechanism is active, agents only consider adopting feedback devices if they are *aware* of them. At adoption, an agent makes the peers that it influences aware of the device. The activation of this mechanism thus becomes an additional degree of freedom to the structure of both models. In the inverse modeling phase of the automation procedure, this will become subject to structural model variation.

AUTOMATED POLICY SIMULATION

In addition to enhancing mechanistic understanding, we assessed the impact of policy actions towards innovation diffusion. A policy (i.e. *"course or principle of action"* (Oxford University Press, 2016)) regarding innovations often aims at directing their diffusion (Jensen and Chappin, 2016). Typically, this is increasing their rate of diffusion.

The above presented automation procedure can automatically project the impact of policies on diffusion. This could be used to test implementations of new policies, as well as the termination of previous ones. The automation phase only uses those models for projections of policy impacts that were accepted based on the inverse modeling phase.

As policies to be tested, we chose two marketing strategies at which free products are given away. (1) After 15 years of device diffusion, an additional 10% of households receive a free water-saving shower head. (2) The same policy is applied, but to those households who influence most other households. These selected households can be framed as households of *opinion leaders*, who are highly connected and influential (Kiesling et al., 2012). They have thus shown particular potential to leverage innovation diffusion (Rogers, 2003; Kiesling et al., 2012; Nisbet and Kotcher, 2009; Van Eck et al., 2011). Simulation of this second policy relies on the explicit modeling of the social network. Consequently, it could not directly be tested by some simulation approaches that lack a modeled social network, e.g. system dynamics.

The tested policies have the potential to promote further adoption of this product by social influence and WOM. Time of policy implementation is 15 years after the beginning of product diffusion. From this point in time, no empirical data were available. Policy simulation thus projects the uncertain future diffusion.

5.4. RESULTS AND DISCUSSION

We conducted two simulation experiments, each representing one of the two automated phases of the procedure.

- Experiment 1 simulates the simulation models from the model library and compares simulation results to the original 'Schwarz' model.

- Experiment 2 demonstrates automated policy simulation with the models that were accepted as sufficiently realistic in the first experiment.

5.4.1. EXPERIMENT 1: INVERSE MODELING

In this experiment, two diffusion models ('Schwarz flexible' and 'Schwarz TPB') were tested for their ability to explain the historical diffusion of water-saving showerheads. This testing is taken out by the inverse modeling phase of the proposed automation procedure. Each of these two models was simulated at two structural variations (with and without the WOM mechanism) and at varied parameters. Simulation results were tested against two empirical patterns: the exponential takeoff of adoption and the empirical market shares of the three consumer groups after 15 years.

The provided matching function that was *minimized* in order to search for realistic models is shown in Eq. 5.2. Mainly, the simulated adoption shares are compared to the provided empirical ones. In the inverse modeling phase, mismatching with empirical market shares is minimized. Further, if the shape of the adoption curve is not exponential, then a significant penalty is added to the matching function. Basis for this is the overall adoption share over all agents and the length of a simulation run of 15 years. Matching results (i.e. best fitness and according parameters) are shown in Table 5.2.

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$$\textbf{minimize}\ \{\text{‘adoption shares’} + 1000 \cdot \text{‘exponential’}\} \tag{5.2}$$

Table 5.2: **Results of inverse modeling phase: best fit and parameterizations.** Optimized fitness for the models 'Schwarz flexible' and 'TPB' with and without word-of-mouth (WOM) is shown. Parameter combinations (except those that resulted in no adoption at all) with best fit are shown: the monthly deliberation probability and social influence (δ_α) in adoption are given for the consumer group 'Leading Lifestyles', 'Mainstream and Traditionals', and 'Hedonists' (s_{LL}, s_{MS}, s_{HD}).

Model	**WOM**	**fitness**	δ_α	$\mathbf{s}_{LL}$	$\mathbf{s}_{MS}$	$\mathbf{s}_{HD}$
'Schwarz'	no	-	0.004	0	0.5	1
'Schwarz flex.'	no	19.12	0.029	0.723	1	0.996
'Schwarz flex.'	yes	5.91	0.013	0	0.679	0.928
'TPB'	no	26.61	0.013	0.288	0.428	0
'TPB'	yes	5.72	0.016	0	0.456	0.200

Results of best matches, shown in Fig. 5.3, revealed that model versions without WOM were less able to match the patterns: the 'Schwarz flexible' model, was not able to generate an exponential pattern, while the 'TPB' model could generate exponential increase in adoption, but was not able to match the adoption data at the same time. With the WOM mechanism being active, both models were able to match both patterns. The only limitation to this matching is a relatively bad reproduction of the empirical market share of the 'Hedonists' group. Based on these results, we regard both simulated models generally suited to explain the diffusion of water-saving showerheads, but only if the WOM mechanism is included.

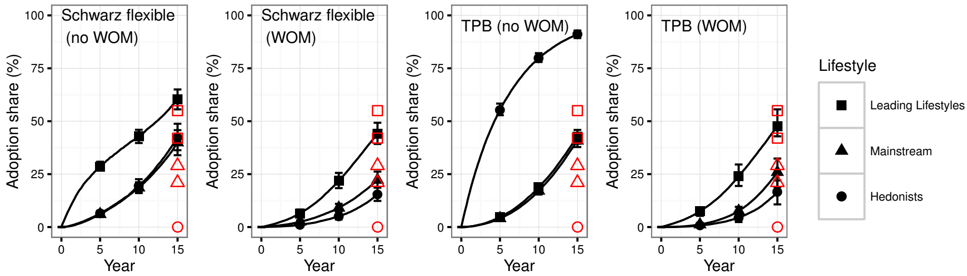

Figure 5.3: **Average adoption of water-saving showerheads, as simulated by the four tested model structured at best matching parameters.** Results are differentiated by consumer group. Whiskers show the quartiles. The hollow points show empirical market shares of the respective consumer group after 15 years of diffusion. For each of the consumer groups 'Leading Lifestyle' and 'Mainstream', two market share data points were used.

5.4.2. EXPERIMENT 2: POLICY SIMULATION

In this experiment, we applied the proposed procedure to automatically assess the impact of a policy on innovation diffusion. This assessment only based on those model variants that matched the empirical patterns in the previous experiment. Instead of testing policy interventions for one simulation model, policies are tested for all models that were thus accepted in the inverse modeling phase. The simulated policies (see Section 5.3.2) are as follows: (1) to give away free water-saving showerheads to 10% of households after 15 years of innovation diffusion; and (2) giving away water-saving showerheads at the same point in time to 10% of households, who are influencing the most other households (i.e. who have outgoing network connections to most other households).

Figure 5.4 and 5.5 show the impact of the assessed policies, which led to the following findings. First, impacts for the two models are relatively similar: giving away free devices at the advanced stage of product diffusion makes the scenarios with and without policy intervention initially diverge quickly. Following the interventions, the innovation spreads at a similar rate, compared to the reference scenario without intervention. Second, for both models, the higher adoption due to the intervention led to a gradual saturation in adoption at the end of 25 years of diffusion. Adoption over time thus forms an S-curve, which is predicted by the Theory of Diffusion of Innovations (Rogers, 2003). This shows that (in this regard), the simulated models are in line with prevailing theory. Overall, the similar additional impact for the two models underlines the robustness of the proposed procedure.

The two assessed policies had a different impact. For both used models, addressing opinion leaders generated a higher impact than addressing random households. Further, the similarity in policy impact for the two simulated models and the difference between the policies is underlined in Table 5.3. It shows the same relative order of impact of the two assessed policies. For both models, the marketing strategy of addressing opinion leaders has a higher impact. Further, the impact of each policy (compared between both models it was tested with) is relatively similar. At this point, it would be possible to extract statistical properties of predicted policy impacts over all tested models. For estimating the expected impact, averaging of predictions would

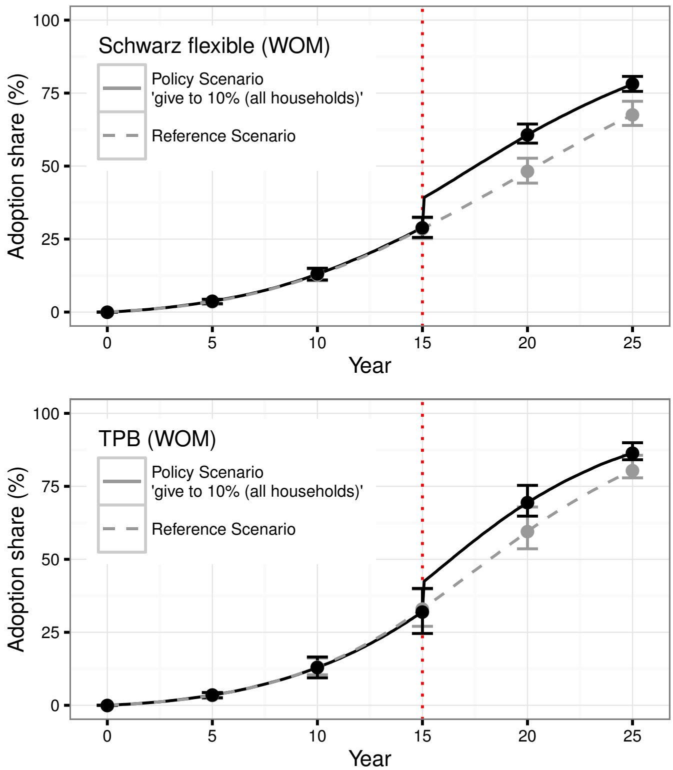

Figure 5.4: **Impacts of policy that addresses all households** (continuous line) compared to baseline scenario (dashed line). Whiskers show the quartiles. Results rely the two most realistic model structures with parameterizations that matched empirical patterns best.

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be advisable. Alternatively, minimum and maximum of such an ensemble would give insights into degree of uncertainty. Overall, this indicates that the policy assessment based on multiple models increased the robustness of the proposed procedure.

5.4.3. LIMITATIONS

Discussion of limitations will focus on two aspects of the proposed automation procedure rather than the application case. This is because this procedure is the key contribution of this study.

(1) The proposed automation procedure might not be applicable to very uncertain processes or models. It appears limited to cases where potential explanations are restricted to a bounded space of options. This is the case for e.g. innovation diffusion. Nevertheless, the proposed procedure has been able to handle structural uncertainty. However, up to which limit such uncertainty can be managed is not known at this point.

(2) The proposed procedure is not easily applicable by everyone. It requires data processing skills in the preprocessing phase. This might limit the circle of potential

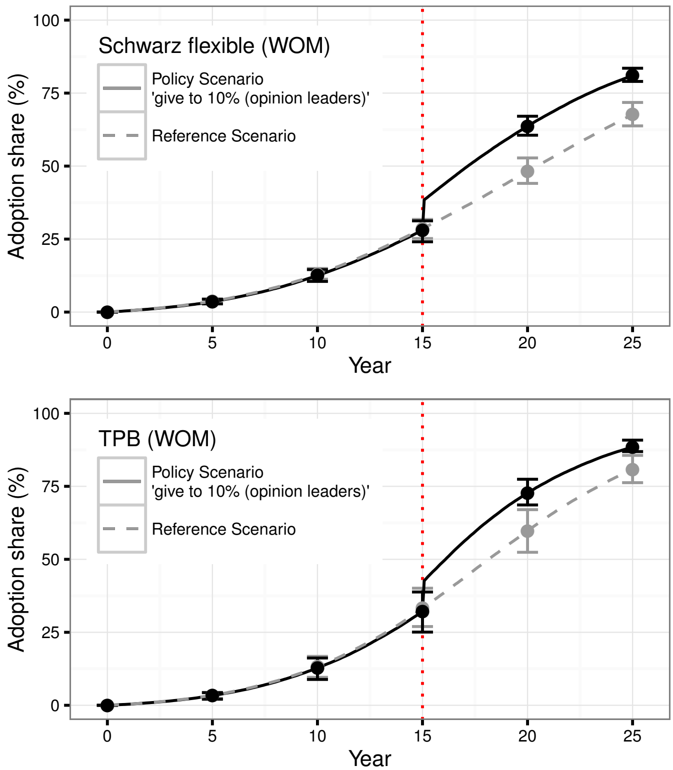

Figure 5.5: **Impacts of policy that addresses opinion leaders** (continuous line) compared to baseline scenario (dashed line). Whiskers show the quartiles. Results rely the two most realistic model structures with parameterizations that matched empirical patterns best.

users. Yet, the procedure still widens this circle of users, compared to the prevailing model building 'from scratch'.

(3) Further, the procedure might require cautious application by the user. Even though the presented method is mostly automated, key decisions still have to be made by the user. This critical role of user decisions is a common feature of automated data-analysis tools, e.g. statistical tests (Strasak et al., 2007). If these decisions are not cautiously made in the presented automation procedure, quality of results might be compromised. For instance, tested diffusion models might be selected by the user without understanding their functioning.

5.5. CONCLUSION

The question guiding this study has been how the generation of agent-based innovation diffusion models can be automated and how this could be useful. This question has been addressed by specifying and presenting an automation procedure to the generation of agent-based models on innovation diffusion and by applying to a case study.

Table 5.3: **Results of policy simulations based on selected, sufficiently realistic models (with word-of-mouth).** Impact is shown as additional percentage of product adoption 15 years after policy implementation.

Model	WOM	Policy	Additional adoption (10 yrs)
'Schwarz flex.'	yes	*'give away to 10%'*	10.5%
'Schwarz flex.'	yes	*'give away to 10% (opinion leaders)'*	13.3%
'TPB'	yes	*'give away to 10%'*	6.0%
'TPB'	yes	*'give away to 10% (opinion leaders)'*	7.7%

Implementation and application of the proposed design showed that the automation procedure is applicable to the diffusion of water-saving showerheads. It further enabled high efficiency of time and labor for this case. This serves as a proof of concept and adds weight of evidence to its suitability to automate the generation of agent-based models of innovation diffusion.

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This application further revealed several advantages of the proposed automation procedure. Present practices of building agent-based models on innovation diffusion are highly diverse. Therefore, it does not seem informative to compare the here proposed procedure against any specific existing practice. Instead, we will conclude on the presented method by re-iterating its advantages. We stress that, in combination, these benefits validate the proposed design.

At application, the procedure proved helpful for improving existing diffusion models from empirical data. The previously empirically validated 'Schwarz model' on the diffusion of water-saving showerheads could be refined to increase its realism. For this refinement, word-of-mouth mechanism of communication between consumers was found plausible—both theoretically and data-wise. This role of word-of-mouth adds weight of evidence to the importance of future marketing efforts that leverage this mechanism.

The rigid use of data in the proposed procedure creates model validation by design. The procedure is driven by comparing model output to empirical data, which is central to validation (Rand and Rust, 2011). Further, systematically comparing multiple models (and mechanisms) enables the good scientific practice of being able to falsify those that can not explain empirical observations. Overall, this has the potential to make agent-based modeling more rigorous than in common practice (Grimm et al., 2005).

The presented approach allows using relatively complex simulation modeling at low complicatedness for the user. Provided a library of potential mechanisms has previously been implemented, a user would only need to provide key data on a dynamic, potentially complex system. The automated procedure then simulates bottom-up models and then tests their matching with the provided data. This procedure selects potentially explaining mechanisms and thus supporting gaining mechanistic understanding.

Due to this relative ease of use, the presented automation approach helps increasing the circle of persons that could independently build agent-based simulation models on innovation diffusion. We see the classical role of the modeler extended by the role of the *user* (also referred to as 'thematician' (Drogoul et al., 2002; Galán et al., 2009)). Such a user can build and apply diffusion models without requiring programming or simulation

skills. Except for extending a library of model components, the commonly required implementation by modelers and computer scientists (Drogoul et al., 2002; Galán et al., 2009) is not required. A user only has to process and provide the required input data, as well as interpret the generated model results. From a perspective of innovation diffusion, we regard this widening of the circle of adopters a crucial service to the spreading of agent-based modeling as an innovative forecasting method.

5.5.1. FUTURE RESEARCH

We suggest to progress this study in three directions.

First, the central phase of inverse modeling is crucial to the proposed automation procedure and could be improved. We propose to support anticipated users of this automation procedure to make good choices on matching functions. For this, different designs of the inverse modeling phase should be compared. Those that are robust in providing good results over several applications cases should be preferred. One such variation would be to withhold for validation some of the data that is now used for model calibration. For choosing between alternating model hypothesis, various statistical approaches should be tested. Candidate methodologies for this are, for instance, Akaike Information Criterion and Bayes factors.

Second, user-friendliness of the procedure can be increased by accepting unstructured input data. The presented application case used structured empirical data. Approaches from data science could allow us to execute the procedure with un-structured data. Overall, increased user-friendliness further increases the circle of potential users.

Finally, we suggest to expand the application of the proposed automation procedure to more cases. This could be facilitated by finding a way for the automation procedure to be as generally applicable as possible. For instance, this could even include generating models from far smaller components than are currently in the modeling library. Application to more cases would eventually help establish *reference models* on the diffusion of innovations, which can further support the development of sound innovation diffusion models.

Overall, we believe these future development and applications will encourage users who are not model builders to apply the proposed automation approach. The here presented design is meant to assist them in exploiting the merits of agent-based modeling of innovation diffusion.

6

Conclusions and recommendations

I love all who are like heavy drops,
falling one by one out of the dark cloud that lowereth over man:
they herald the coming of the lightning,
and succumb as heralds.

Friedrich Nietzsche

6.1. Conclusion

Reducing domestic heating demand is an attractive contribution to the reduction of greenhouse gas emissions. Feedback devices, if diffusing successfully among consumers, could trigger the behavior change in heating that would significantly contribute to this. This thesis used simulation modeling to estimate the potential diffusion of such devices. It also estimated the behavior change of device users and the diffusion of the behavior change that this creates. Based on capturing these diffusions, the potential impact of devices, i.e. their overall effect on energy-conservation behavior, could be simulated and analyzed.

With these simulations, it is possible to inform policy makers and stakeholders on how to support the impact of feedback devices. Their actions could potentially amplify or diminish the realization of the potential that is inherent to behavior-changing feedback devices.

This thesis set out to develop a simulation study design for agent-based modeling to tackle these tasks. Ideally, this design would overcome the current limitations of agent-based modeling, which often requires cumbersome and somewhat arbitrary decisions on model design. From this motivation emerged the central research question of this thesis:

How can the impact of behavior-changing feedback devices on energy-consumption

behavior be systematically simulated?

This section gives an answer to this question. This includes providing methodological recommendations to modelers, as well as practical recommendations to policy makers. Eventually, this chapter will reflect on limitations of this thesis, and will highlight emerging future challenges.

The central research question of this thesis has been addressed in detail in four sub-questions. Their succession inspired a stepwise research approach, which dedicated to each sub-question one step. The first three of these developed methods simulated the impact of behavior-changing feedback devices. They started at identifying the mechanisms of co-diffusion, modeled empirically-grounded impact of devices, and eventually assessed policy strategies systematically. In the fourth step, these methods could eventually be standardized as a procedure of automatically generating agent-based diffusion models and assessing the impact of policies on diffusions. In the following, the lessons learnt during these four research steps will be presented. Based on these insights, an overall conclusion on the central research question will then be drawn.

6.1.1. CONCLUSION 1: MECHANISMS OF IMPACT OF FEEDBACK DEVICES

As a first step of this thesis, the general dynamics of interaction between the diffusions of feedback devices and energy-efficient heating behavior were analyzed. This addressed the following question: *What are the mechanisms via which feedback devices can change heating behavior?*

Conclusion 1 – In addition to the diffusion of feedback devices, the diffusion of energy-efficient behavior enhances the overall impact of feedback devices on heating behavior. Consequently, behavior diffusion is confirmed as an important component to this co-diffusion of technology and behavior. This is in line with previous research on the potential of behavior diffusion to spread energy-efficient behaviors (see Peschiera et al., 2010; Chen et al., 2012; Anderson et al., 2014). This motivates behavior diffusion to be considered at future assessments of feedback devices.

Two mechanisms were identified via which behavior diffusion increases the overall effect of feedback devices. First, behavior diffusion was found to spread energy-efficient behavior from households, who changed their behavior due to feedback, to others. By thus reaching non-adopters of devices, behavior diffusion decreases difference in behavior between adopters and non-adopters of feedback devices. Second, behavior diffusion was found to speed up the overall behavior change from feedback devices. Due to behavior diffusion, one feedback device reached more households (e.g. the peers of device users). This makes the impact of each device stronger and thus overall behavior change faster.

Behavior diffusion can be regarded to thus create a positive externality to the diffusion of feedback devices. As changed behavior can spread from households that use feedback devices, more households can indirectly benefit from this feedback. This can be attributed to behavior change and will not be found at energy-efficiency devices that do not create behavior change. For instance, home automation (e.g. ‘smart’ adaptive

thermostats) can save energy, but would not incentivize behavior change that could be leveraged by behavior diffusion.

Consequently, behavior diffusion should be included in the assessment of behavior-changing feedback devices. This is because it has the potential to reinforce the impact of feedback devices significantly. This further motivated measuring the relative importance of this process in the following steps of the research approach.

6.1.2. CONCLUSION 2: PROJECTED IMPACT OF A FEEDBACK DEVICE

The second step of the research approach quantified the relative importance of the modeled processes. The abstract modeling approach from the previous research step could not measure this with reasonable certainty. For doing so, an empirically-grounded modeling approach was needed. The co-diffusion framework of this thesis was therefore applied to an empirical case. This aimed at answering the following sub research question: *What is the impact of the diffusion of feedback devices and the diffusion of the behavior that they incentivize?*

Conclusion 2 – The overall effect of a case feedback device—scaled up by device diffusion and the diffusion of energy-efficient behavior—was found to be of significant importance. Its projected effect was predominantly caused by the diffusion of feedback devices and less so by behavior diffusion.

Overall, the diffusions of a feedback device and that of the behavior it creates was found to cause a significant impact. These diffusions were further estimated to successfully scale up the effect of the case technology 'CO_2 meter' in the case city Bottrop (Germany). Accordingly, 15 years after the start of successful device diffusion, energy-efficient ventilation would have increased by an additional 12 (6–18) percentage points. Based on experience with proxy innovations, this impact is expected to differ between social groups. The early adopters of feedback devices can be expected to be of higher social status.

Diffusion of a device, including the direct feedback to its users, was found to be the main component of its impact. Contribution of this process showed to be the larger than that of behavior diffusion. This emphasizes the key role of device diffusion: this diffusion is not just necessary for feedback devices to have an impact at all—it also appears to be the most important effect component.

Conversely, diffusion of energy-efficient behavior was also found to have an important contribution, but of second rank. The relative contribution of behavior diffusion to the overall effect of the assessed feedback device ranged from 12% to 46%, depending on the social group. The lower the social status of a household, the higher the relative importance of behavior diffusion. Consequently, neglecting the impact of behavior diffusion would underestimate the impact of feedback devices significantly.

To practitioners, this suggests that efforts of increasing the impact from feedback devices should focus on supporting device diffusion over behavior diffusion. These efforts could be most effective when focusing on households of higher social status, who are most interested in using feedback devices. From these early adopters, devices and energy-efficient behavior could then 'trickle down' to other social groups.

6.1.3. Conclusion 3: Policy recommendations

The previous research step analyzed the diffusion of feedback devices, but did not factor in the effect of policies that may support feedback devices. The following step therefore explored ways in which the diffusion and impact of feedback devices could actively be supported. Based on the previously developed empirically-based simulation model, policies towards this end were assessed in simulation experiments. By assessing these marketing strategies, this study addressed the following question: *How can the projected impact of feedback devices be affected by policies?*

Conclusion 3 – Marketing of feedback devices was estimated to have a significant impact on their projected impact. Marketing strategies of lending out or giving away feedback devices for free, and of targeting households who are of high social status or Opinion Leaders, were found particularly effective and cost-efficient. Marketing campaigns showed to increase projected adoption of energy-efficient ventilation by an additional ca. 21% of households over 15 years. However, changing the location of their implementation did not significantly affect the impact of marketing campaigns.

In this thesis, marketing strategies have been found as attractive options to support the overall impact of behavior-changing feedback devices. When addressing the previous sub-questions, the diffusion of feedback devices showed to be of particular importance for the eventual decrease in heating demand. If marketing is able to persuade an initial set of households to adopt devices, word-of-mouth can drive more households to adopt the same devices. This can then trigger the other processes discussed in this thesis: i.e. households undergoing behavior change due to feedback and the diffusion of energy-efficient behavior.

Comparison of marketing strategies showed that lending out devices, giving away free devices and targeting socially well connected households are particularly effective at triggering the largest effects. Simulation was used to systematically compare the effectiveness of marketing strategies from the general categories *economic incentives*, *promotion*, and *placement*. Lending out feedback devices for three months each was found the most effective strategy. This strategy also appears to be highly practical because only a limited number of devices needs to rotate among households. Likewise, initially giving away a limited number of free devices to households was also effective. Further, targeting different social groups was relevant for the effectiveness of marketing. The higher the social status of a household, the more effective targeting it via marketing appeared. Moreover, targeting households that are socially well connected (so-called ‘Opinion Leaders’) appears particularly effective. Conversely, raising awareness about the availability of feedback devices was generally found the least effective. The only exception to the low effectiveness of raising awareness was when this marketing strategy was targeted to Opinion Leaders and households of high social status.

When comparing the impact of marketing strategies regarding their *cost-efficiency*, they rank differently. Due to its low cost, raising awareness of the availability of feedback devices is of highest cost-efficiency—particularly when targeting households of higher social status. Lending out feedback devices was second best regarding cost-efficiency because one device can be lent out to multiple households. Leveraging Opinion

Leaders was estimated to be less cost-efficient because their training is expected to be expensive. Finally, giving away a limited number of free devices was found the least cost-efficiency—with the only exception of when households of higher social status were targeted.

These results were found to be generalizable between neighborhoods and cities of implementation. Regarding neighborhood of policy implementation, spatially focused marketing did only lead to a local increase in impact from feedback devices. But changing the place of marketing did not alter the overall behavior change from feedback devices on a larger spatial scale. Likewise, simulation results were also not sensitive regarding spatial structure of a modeled city. This lack of sensitivity to spatial variation suggests that the essential dynamics of co-diffusion of technology and behavior do not heavily rely on detailed spatial structures. Consequently, the use of commercial socio-demographic data of high resolution will not always be needed for future, comparable simulation studies.

6.1.4. CONCLUSION 4: AUTOMATING INNOVATION DIFFUSION MODELING

The final step of the research approach aimed at making agent-based modeling less costly in time and labor. This made use of the methods from the previous steps. Previous model development and application in this thesis was principally taken out manually. At the time of writing, this was common practice in the field of agent-based innovation diffusion modeling. To make these tasks more systematic, automation was applied. Thereby, the following question was addressed: *How can innovation diffusion models be developed and applied more systematically?*

Conclusion 4 – Innovation diffusion models can be developed and applied more systematically by the use of automation. This was realized by an automation software prototype that uses a standardized procedure to select model components that fit a given innovation diffusion case. This makes building and using agent-based innovation diffusion models more systematic and less costly in time and labor.

Realizing the presented automation approach was possible due to three factors: existing models candidates, their ontological similarities, and data availability. First, the multitude of available agent-based innovation diffusion models provides a high variety of potential mechanisms of innovation diffusion (Kiesling et al., 2012). The presented automation procedure draws on this diversity. Instead of requiring the generation of entirely new mechanisms, simpler testing of explanations from previous models is possible. Second, most existing agent-based models of innovation diffusion are ontologically similar (Kiesling et al., 2012): they have a shared understanding of objects, concepts, and other entities that are modeled (van Dam et al., 2012). This makes it possible to use them as exchangeable modules in a meta-model. Modularization in the automation software was able to directly map this modularization of models. Finally, the data-driven approach of the automation procedure required historic diffusion data. Because innovation diffusion is a well-established field of research, data on this process was available.

This approach showed to be successful at speeding up model generation and making the modeling process more systematic. Gain in speed was one of the design requirements that motivated automation. Further, automation aimed at making the modeling process more systematic. The presented case application on the diffusion of water-saving shower heads showed that both targets could be met. Overall, this proof of concept underlines that the chosen automation approach fulfilled its purpose and success.

6.1.5. OVERALL CONCLUSION

The previous conclusions on the sub research questions provide the foundation to answer the central research question of this thesis: *How can the impact of behavior-changing feedback devices on energy-consumption behavior be systematically simulated?*

Overall conclusion – The impact of behavior-changing feedback devices on energy-consumption behavior can be analyzed systematically by simulating the co-diffusion of these devices and behavioral change. This relied on four pillars. First, assessment of impact based on developing and simulating the framework of co-diffusion of technology and behavior. This generalized the understanding of the potential impact of feedback devices. Second, the initially abstract model analysis was refined by empirical data. Third, the thus developed empirical-baed model allowed to assess the potential of policies to influence the impact of feedback devices. Fourth, automation made assessment of this impact more performant and accessible. Overall, this improves the way agent-based models of innovation diffusion models are developed and applied.

Systematically assessing feedback devices via the framework co-diffusion of technology and behavior proved to be fruitful. Dynamics of the impact of feedback devices confirmed that it has been worthwhile to include both these diffusions in the assessment. A further benefit of the co-diffusion framework was the possibility to operationalize it for agent-based modeling. Doing so allowed to simulate and scale up findings from field tests of feedback devices.

Scaling up the impact of feedback devices via simulation confirmed them to be suited to tackle low-hanging fruits of energy-efficiency in buildings. For households that use feedback devices, these achieve average energy savings of ca. 8% (Karlin et al., 2015). Conversely, upscaling the impact of a device with this impact to the city level projected overall savings of 1%–2%. These overall savings are significantly lower, but still have to be seen as worthwhile because they come at low cost and high scalability.

The need to reduce heating energy consumption by far more than this projected 2% calls for a combination with other approaches. The roll-out of feedback devices needs to be combined with e.g. upgrading the insulation of existing buildings. Connecting these approaches will be useful because the expected future increase in building insulation will also increase the relative importance of user behavior in energy consumption.

The automation procedure presented in this thesis further improved performance of developing agent-based innovation diffusion models. Having sped up the development of innovation diffusion models via automation frees resources during the model building

process. These can be used by modelers to test a greater variety of model explanations for observed phenomena. Additionally, automating model generation reduces the need for programming skills on the side of the modeler. This, in turn, widens the circle of persons that can apply agent-based modeling to better simulate and shape diffusions of innovations.

Finally, the presented automation procedure progresses the method of agent-based innovation diffusion modeling by making it more rigorous. First, this is done by achieving 'validation by design' of the generated diffusion models. This relies on the strict comparison of the generated models with empirical data, assuring that these successfully represent real-world processes. Further, this strictly in-built model validation contributes a systematic method to model comparison and falsification. Given empirical data of an innovation diffusion, the automation procedure guides the comparison of realism between model candidates. This automated comparison makes it easier to identify plausible models and to take out the good scientific practice of falsifying less plausible ones.

6.2. LIMITATIONS AND FUTURE RESEARCH

Regarding the undertaken research approach, limitations are of three kinds: model uncertainty, limitations of model application, and limitations of the presented automation approach. For each of these limitations, it is further proposed how to tackle these.

6.2.1. MODEL UNCERTAINTY

Uncertainty is fundamentally inherent to simulation modeling. Modeling is a simplification and an abstraction from reality, due to which realism naturally has to be reduced. Therefore, it can be regarded impossible to eliminate limitations to model realism. If models, which can only be built based on yet existing knowledge, are used to predict the future, their uncertainty might further increase. Consequently, there are potentially unlimited facets of model uncertainty and limitations to model realism.

Despite this fundamental uncertainty, when using a model to design solutions that would work in reality, it is still possible to make it useful for this task. To Pablo Picasso are attributed the words *"Art is a lie that helps us see the truth."* The same has been said about simulation modeling. Accordingly, the way models are used can compensate for their inherent uncertainty.

In the following will be reflected on the three main model uncertainties in this thesis—and it will be shown how modeling has still been made useful for these cases. First, limited empirical data from field tests of feedback devices might have affected the quality of results. Based on the available data, the energy savings from the case technology 'CO_2 meter' were estimated as 8%. This figure lies within a range of plausibility, but it might change with future insights. Fortunately, because this uncertainty propagates linearly, results can readily be adjusted in the future. Second, consumer choice on energy-efficient heating behavior was modeled to happen equally across lifestyle groups, which might not be the case in reality. Conversely, choice on feedback device adoption was modeled heterogeneously, based on experience with

proxy innovations. This difference suggests that also heating behavior might diffuse heterogeneously through society. Future field research has the potential to provide the empirical insights into this. At this point in time, social structure of diffusion decisions was modeled as detailed as available empirical data allowed for. Finally, an important part of this thesis is subject to the inherent uncertainty of future projections. Even though methods were applied to estimate the future success of feedback devices (e.g. using proxy-innovations and surveying), projecting the future diffusion of a yet to be marketed innovation is fundamentally uncertain. The way the simulation models were used had to cope with this uncertainty. For instance, it had to be made clear that the projected successful diffusion of a device is a mere assumption. Instead of predicting *if* a device will diffuse, it is rather suited to show *what happens if* it does. Additionally, generating findings from a large ensemble of varied simulation runs and potential futures helped to cope with this uncertainty.

The realism of the simulation models that were developed in this thesis can be further increased. This will have the benefit of decreasing model uncertainty. Consequently, transfer of insights from models to reality will be strengthened. Ways how this could be achieved are presented in the following section.

Empirical analysis of social influence Collecting data on how society influences energy consumption of individual persons is challenging, but valuable. In this thesis, qualitative data from interviews and surveys on the level of individual households was used to *directly* model the mechanisms by which social influence takes place. Quantitative observations on the aggregated, societal level were used to *inversely* model the rate of this change. A missing link between these data sources is quantitative behavioral data of connected groups of individuals that is of high detail. Ideal data to fill this gap would be time line data of behavior of persons that also frequently interact with each other in person. These data would appear suited to better understand and model interpersonal influence on energy consumption behavior.

Capturing behavior with higher temporal resolution Similar to data on social influence of higher quality, it would be valuable to use behavioral data of higher temporal resolution. In this thesis, behavioral data from field research were aggregated to the mere probability that a feedback device creates some behavior change among its users. This aggregated figure was then directly integrated in the simulation models. Instead, it would be valuable to gain deeper empirical understanding of the process of behavior change from feedback. This would also include detailed behavioral mechanisms, such as relapse of behavior to the level prior to a feedback intervention. Capturing this phenomenon was not possible in this thesis, just the same as in previous research (see Chen et al., 2012). These insights would require behavioral data of high resolution and therefore would become possible if this data were available.

Modeling more kinds of behaviors With additional data on energy consumption behavior, behavior could also be modeled with greater detail. In this thesis, room ventilation was modeled as binary: households would either adopt energy-efficient ‘shock ventilation’ or not. This was due to the focus on shock ventilation, but also due

to limited empirical data. When increasing resolution of behavioral data, feedback on the impact of behavior changing feedback could be modeled better. For example, a transition from different ventilation behaviors to ‘shock ventilation’ might be of different ease and therefore different likelihood. Therefore, capturing more ventilation behaviors with modeling could be worthwhile. It would also be beneficial to model the duration of ventilation, as this is an important factor to effectiveness and energy-efficiency of ventilation.

More detailed decision on device adoption It appears promising to increase the detail with which decisions on device adoption are modeled. In this thesis, this is done based on a previously validated, but rather simple decision model. At increased detail of decision modeling, it will become possible to model more types of interventions. For instance, if numerous relevant consumer preferences regarding the decision making process on adoption are modeled, it could be derived how changes to these preferences would affect adoption choice. Via simulation could additionally be projected the overall effect that such interventions would have on the diffusion of feedback devices and their scaled-up impact.

6.2.2. LIMITATIONS OF MODEL APPLICATION

The chosen research approach led to further limitations in model application. This showed in the limited number of case studies and restrictions in testing policies.

First, work in this thesis focused on exploring the impact of feedback devices via simulation, which limited resources for generating empirical insights. This led to the circumstance that only one case of a feedback device and only one type of energy conservation behavior was examined in depth. Consciously accepting this limitation allowed to instead prioritize the development of multiple simulation models and the progression of computational methods.

Second, some potential policies could not be assessed, due to the chosen model structure. For instance, addressing specific preferences of consumers was not possible. This was because they were not modeled in great enough detail. Instead, the tested marketing strategies had to address other aspects (i.e. price, promotion, and place).

Model application can be extended, to address these limitations. The following paragraphs present options for this.

More cases of feedback devices A central future application of the developed simulation models could be their application to more cases of feedback devices. More experience could be gained on the temporal dimension and on the magnitude of overall impact from feedback devices. Finally, policy recommendations would become more robust with more cases and the simulation based assessment of policies would have a stronger foundation.

Assisting the design of feedback devices The simulation models presented in this thesis have the purpose to assess the impact of *existing* feedback devices. Instead, these models could also be used to assess the impact of *hypothetical* devices. These assessed hypothetical devices could be prototypes or early design drafts. In iterations

between drawing board and simulation, ex-ante assessment via simulation would assist the design of future feedback devices that can more effectively create behavior change.

Exploring synergies with other policies The policies that have been assessed in this thesis were exclusively dedicated to support the diffusion of feedback devices. In addition to such policies, it would be attractive to concurrently test policies regarding other aspects of energy efficiency. For instance, one important set of policies to lowering energy consumption in buildings is energy renovation. Energy renovation is an overall crucial contribution to reducing heating demand. But it has repeatedly been observed that energy-efficiency of heating behavior decreases after such renovations. Therefore, feedback devices could be used to support energy-efficiency of heating behavior after an energy renovation. A coupling of the simulation models from this thesis with simulation models on renovation decisions, for instance, would make it possible to assess such synergy between policies.

6.2.3. LIMITATIONS OF THE AUTOMATION APPROACH

Finally, also the presented approach of automated generation of innovation diffusion models has its limitations. It faces some limitations regarding the applicability to cases and at extending the circle of users.

The applicability of the presented automation procedure to particularly uncertain cases of real-world processes might be limited. The procedure has shown to work well for the diffusion of a novel product in society. The success of this procedure relied on the following factors: the availability of several simulation models, a shared understanding by these models on the modeled system, and the availability of data on the modeled process. Consequently, application to further cases of innovation diffusion appears feasible, whenever data are available. To cases where these conditions are not met, an automated modeling approach might not applicable.

Further, even though the intention of enabling automated modeling is to extend the circle of users, this could only be achieved to a limited degree. The central reason for this limitation is that taking out the presented procedure requires data processing skills and at least basic understanding of simulation models. Data processing skills are required to create the required input. Additionally, even though the model building is automated, the user has to guide the software to create meaningful results. This critical role of user decisions is a common feature of automated data-analysis software, e.g. statistics tools. Even though the presented approach widens the circle of potential users, these requirements for them limit their number.

These limitations can be addressed by future research. Building on the presented procedure for the automated generation of agent-based models of innovation diffusion bears significant potential.

Additional cases of feedback devices Having developed a way to automatically generate and apply simulation models on innovation diffusion will facilitate modeling the diffusion of more feedback devices. With model building being automated, users will be able to focus on only providing required data on their diffusion or suited proxies. Thus, applying agent-based modeling to the assessment of more feedback devices will

be relatively time-efficient, compared to repeated manual model development 'from scratch'.

Identifying reference models on innovation diffusion Being able to automatically test many diffusion models against the same set of empirical data will make it possible to identify *reference models* of innovation diffusion. A current limitation in the field of innovation diffusion modeling is the multitude of simulation models. At this point in time, it is not clear which of the theoretical explanations contained in the numerous innovation diffusion models has the widest applicability. This thesis contributes to the field of agent-based innovation diffusion modeling by presenting the procedure that is capable of falsifying models for specific cases of innovation diffusion. Future research that applies this procedure to many cases might be able to find out what diffusion model works under what system characteristics.

Improving automated inverse modeling Also technical improvements to the presented automation approach appear to be of significant potential. In the presented automation procedure, the inverse modeling phase is crucial. Its potential for improvement should therefore be further evaluated. The now used 'simulated annealing' optimization technique could for instance be compared to other optimization approaches. One criterion of comparison could be how robust result quality is (e.g. against user decisions in the matching function).

Generating simulation models from atomic components One particularly attractive improvement to the automation procedure would be generating innovation diffusion models without requiring a library of complete decision model candidates. The presented automation prototype requires entire decision models to be stored as components in a pre-defined model library. This has the disadvantage of redundancy: mechanisms such as word-of-mouth have to be implemented for each component in the library. Instead, these models could be broken down to the smallest possible sub-models that could be re-assembled at runtime of the automation procedure. Each mechanism (e.g. word-of-mouth) would become one of these models components. Based on data, components could then automatically be combined to models, similar the way decision trees are 'grown' and 'pruned' in the field of machine learning. Thus, reducing the size of the required components in the model library would potentially reduce the effort of extending the model library.

Increasing user-friendliness Finally, it would be worthwhile to invest time into greater user-friendliness of the presented automation approach. For now, the automation software is at the stage of a proof of concept. Because it has the potential to be applied by non-programmers, it could also be made even more accessible to them. First, data analysis tools could be integrated on the input side of the procedure that might make it possible to automatically build models directly from unstructured input data. Further, to support users at selecting diffusion models and policies to be tested, a graphical user interface could also be beneficial. Finally, more detailed reporting could make the approach more transparent to laypersons. Overall, it is to be expected that

these improvements have the potential to further support the anticipated adoption of agent-based modeling by non-modelers in order to allow them to better understand and shape innovation.

6.3. REFLECTION

In the following, this thesis will reflect on lessons on adequate complexity of modeling innovation diffusion. Thereafter, an outlook is given on future models in forecasting and on the democratization of predictive modeling.

6.3.1. COMPLEXITY OF AGENT-BASED INNOVATION-DIFFUSION MODELS

There exist two schools of thought that each propose use of either simple or complex agent-based models. Both views have valid arguments, making it difficult to side with only one of them. On the one hand, it is advocated to use *simple* models that avoid overfitting real-world phenomena by capturing only the most important driving factors. On the other hand, other modelers propose to use models that are *descriptive* by capturing the modeled phenomena more intuitively, but are also more complex.

The automation approach presented in this thesis offers a third way. The presented approach informs on adequate model complexity by making rigorous use of empirical data. By testing models of varied complexity against data, it informs users which model complexity is adequate to explain a real-world phenomenon. This complements the somewhat arbitrary intuition of modelers with systematic benchmarking against data.

6

The presented automation approach assists modelers in choosing between simple and descriptive models. Furthermore, the automated approach facilitates the parallel development and application of multiple models. Without significant added effort, modelers can both develop simple and descriptive models in parallel. With this multi-model approach, modeling can draw on both these worlds to create the best model *ensemble*. Thereby, it is useful that all of the agent-based models generated by the presented automation approach are close to theories and are black boxes (as e.g. current deep learning models). Consequently, a multi-model approach has the benefit of providing complementing mechanistic explanations of the modeled innovation diffusion.

6.3.2. FUTURE MODELS IN FORECASTING

One of the take home messages of this thesis is that there is great potential to improve the quantitative models used in forecasting. While building these models is up to future research, it is already possible today to describe design targets for them. The following section proposes a direction into which to develop these models for forecasting.

Such outlook can directly build on existing modeling paradigms, which each have some desired traits. A desirable forecasting model would show the following four signs. It would be highly predictive, quick, user-friendly, and informative. First, being – within the inherent limitations of this undertaking – highly predictive is a key property of a powerful forecasting model. A current modeling paradigm that is strong at this is deep learning. Second, model development and application should also be quick. This is currently achieved by statistical models. But given the emerging cloud

computing infrastructure, parallel computation is becoming a valid alternative means. Third, a forecasting model should be user-friendly. This trait is commonly found at automated statistical software packages. Finally, a model should be informative about the mechanisms on which forecasting relies. This is a property at which agent-based models are currently strong.

Future research should aim at combining these advantages. In contrast to biological evolution, the evolution of technology is easily capable of recombining technologies, even if they have evolved significant differences (Kelly, 2010). This emphasizes the feasibility of cross-learning between the different modeling schools in forecasting. The ingredients for the next generation of forecasting models are there. Now, they need to be put together.

6.3.3. DEMOCRATIZING PREDICTIVE MODELING

We are moving towards a digital society that generates and finally can make use of vast amounts of data. These data can be generated on virtually every aspect of our lives. Due to the mega trends of Internet of Things and Quantified Self, this includes also detailed data of individual persons. Such fine grained data can be used for generating 'what-if scenarios and predictions on these persons. But one of the key questions regarding this is who should be able to do so.

An important challenge for the future is to democratize this technological potential. Presently, there exists a large divide between leading tech companies and individual persons. Many state-of-the-art businesses make use of model-based analytics. Conversely, almost no individual person does. Empowering laypersons to analyze their personal 'data trails' would help closing this digital divide.

To achieve democratization of predictive modeling, model-based analytics needs to become more accessible to these individuals. Models need to become easier to use and their results need to become more intuitive. They also need to be highly flexible regarding their input data. Achieving this would increase the society-wide use of *self service* analytics. Only then would it be possible to maximize the total value that society generates from this technology.

A

MODEL DESCRIPTION

In the following, the agent-based model developed in this paper is described using the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2010).

PURPOSE

The purpose of this model is to investigate the effect of behavior-changing feedback devices on heating behavior by capturing the diffusion of technology and behavior among households communicating on technology adoption and energy consumption behavior. Both processes are combined in one model to explore their relative importance on the overall effect of behavior-changing feedback technology.

ENTITIES, STATE VARIABLES, AND SCALES

Central entities of the model are agents that represent individual households in one city. Each household agent has three static attributes. First, an agent is of one of five sociological lifestyles (Postmaterialists, Social Leaders, Traditionalists, Mainstream or Hedonistic lifestyle) defining its preferences to adopt environmental-friendly household technology (see Schwarz and Ernst, 2009). Second, agents have a set of social ties to other household agents, their peers. The number of peers is based on empirical observations (see Fig. 2.3). Third, each household has a static position in the two-dimensional space. Location defines the likelihood peers are linked with one another, because spatial proximity makes a link between two households more likely (Holzhauer et al., 2013).

Additionally, each household has two dynamic state variables. First, a household has either adopted technology or not, represented by a binary variable. Second, a household has a specific energy consumption behavior. Here, we defined this as the mean space heating temperature, with unit °C.

Temporal resolution of the model is monthly time steps from January 1990 to December 2019.

Spatial resolution is abstract. Households have a random and fixed position in a two-dimensional rectangular plane with side length of 100 continuous spatial units. This

plane does neither wrap to a cylinder nor torus, but represents a well-delimited spatial area, such as a city.

PROCESS OVERVIEW AND SCHEDULING

The model consists of the sub-models 'technology diffusion', 'feedback effect' and 'behavior diffusion', which are executed successively at each time step. Within these sub-models, agents change their state variables concurrently, i.e. their future states are partly influenced by the state variables of their peers at the previous time step. Model initialization, steps, and sub-models for each time step are as follows:

1. Initialization
2. WHILE ($t < t_{max}$):
   (a) Technology Diffusion
   (b) Feedback Effect
   (c) Behavior Diffusion

DESIGN CONCEPTS

Basic principles applied in the model are mainly four scientific theories. First, Diffusion of Innovations Theory (see Rogers, 2003) is applied as a general model guideline. It contributes to representing the spread of technology and behavior innovations when potential adopters interact. Thereby, Rogers' distinction between earlier and later adopters is captured by the different decision making of the five sociological lifestyles for adopting feedback technology. Second, Social Network Theory is applied by connecting households in a social network graph. This graph defines social ties between households, among which these communicate. This informs agents of the adoption and energy consumption behavior of their peers. Consequently, social influence can affect the households' decisions in these realms. Third, technology adoption is partly based on the Theory of Planned Behavior (see Ajzen, 1991). This decision theory underlies agents' decision to adopt technology. According to this theory, an innovation adoption decision depends on both the adopter's preferences and her peers' decisions (Rogers, 2003). Finally, behavior diffusion is based on Social Learning Theory (see Bandura and McClelland, 1977), which suggests peer behavior influences energy consumption behavior of households.

Emergence occurs through the diffusions of technology and behavior. These diffusions are macro processes based on adoption decisions at the micro level, i.e. the level of agents.

Sensing of household agents occurs through social ties of the social network graph. Agents perceive which of their peers adopt feedback devices and what temperature they set for heating. This sensing of peer behavior marks the origin of social influence.

Interaction occurs through social influence between household agents sharing relationship links. For technology diffusion, adopting peers increases the probability (where this equals not already 1) a household adopts feedback technology. For behavior diffusion, a household agent gradually adapts its energy consumption behavior according to the mean behavior of its peers.

Objectives of household agents drive their choices on technology adoption or energy consumption behavior. Agents adopt feedback devices if it incurs a relative advantage over not adopting. Inspired by the Theory of Planned Behavior, this decision can be influenced by the number of adopting peers. For behavior diffusion, household agents follow objectives: habituality and conformity. With no social influence, household agents habitually practice their previous behavior. Social influence, however, motivates behavioral change towards the mean peer behavior. The strength of this social influence is defined by s_i, the households' susceptibility to behavioral change (see below).

Adaptation appears when agents' make different decisions at varying levels of social influence. All peers of a household supporting a certain decision can increase the likelihood this household makes the same decision.

Stochasticity occurs in three aspects. First, location of agents and their social network are initialized randomly. Second, each time step agents have a random probability to consider technology adoption. Finally, the lifestyles Mainstream, Traditionalists and Hedonists do not decide on technology adoption by deterministic deliberation, but by applying the so called 'take-the-best' heuristic.

Observations lead model design decisions on the social network topology, preferences to adopt technology, and energy consumption behavior. From interviews on ego-networks of communication on energy consumption behavior, provided by Baedeker Baedeker (2014), have been derived the degree distribution in the social network (see Fig. 2.3) and the probability of a network tie to be of short spatial distance ($p_{NBHD} = 0.5$). From surveys on the mean space heating temperatures in British households by Shipworth et al. Shipworth et al. (2010), the initial energy consumption behavior is set to 21.1°C. The technology adoption decision of agents is based on extensive surveying conducted by Schwarz Schwarz (2007).

INITIALIZATION

Model initialization follows three successive steps: creating household agents, generating the social network and setting the adoption state variables of the agents.

Initialization creates N household agents. Each agent is assigned a random location and a random lifestyle, weighted by an empirical distribution (see Table 2.1).

The social network is built on two empirical foundations. First, we extract two statistical ego-network properties from interviews with households about energy consumption behavior (Baedeker, 2014). These properties include the 'degree distribution' of network nodes (see Fig. 2.3) and the probability relevant communication within a city occurs in the same neighborhood ($p_{NBHD} = 0.5$). The second theoretical foundation is members of a certain sociological lifestyle communicate more with members of the same lifestyle. We developed an algorithm that was inspired by Watts and Strogatz Watts and Strogatz (1998) to generate a social network that meets these empirical characteristics:

1. Assign a degree target $deg^*(i)$, i.e. the ideal number of peers of each agent, for fitting the overall degree target distribution to the empirical degree distribution.

2. Create a number of links equal to the respective degree target by repeatedly applying for the agents with fewer assigned peers than their degree target:

A

(a) Randomly choose lifestyle with which to connect (probability to connect to own lifestyle is set by the homophily-probability h, while all other lifestyles share the residual probability equally).

(b) Connect to a random agent of the chosen lifestyle, who has less peers than its degree target and who is closer than d_{NBHD}.

3. Remove each relationship link with a probability (1 - p_{NBHD}).

4. Repeat step 2 with the altered constraint forging connections between agents with distance *greater than* d_{NBHD}.

Finally, the adoption state variables are initialized for all agents. Household agents are assumed not to initially adopt feedback technology. The initial energy consumption behavior (y_{i,t_0}) is homogeneously set to 21.1°C for all agents, based on the mean of space heating temperatures observed by Shipworth et al. Shipworth et al. (2010).

SUBMODEL: TECHNOLOGY DIFFUSION

This submodel represents the decision framework for agents to adopt technology, which based directly on the empirical-based model presented by Schwarz Schwarz (2007).

Agents have a fixed probability at each time step to decide on adoption (δ_α). When deciding, the adoption decision is modeled to be qualitatively different between lifestyles. For some lifestyles, i.e. Postmaterialists and Social Leaders, surveying shows that they trade-off many criteria when deliberating on adoption Schwarz (2007). The decision for these lifestyles is thus modeled on rational deliberation, similar to the Theory of Planned Behavior (see Ajzen, 1991), but without underlying social influence. Conversely, Hedonists, Mainstream, and Traditionalists generally consider fewer criteria when deciding on technology adoption. Thus, agents of these lifestyles are not deliberating rationally on technology adoption, but apply the so-called *take-the-best* heuristic (Schwarz, 2007, see). They decide according to the most important stated decision criteria that clearly favor one choice option. Two decision criteria with the same stated importance are processed in a random order. If this heuristic does not lead to a clear decision, agents imitate the majority of their peers.

We parameterized the decision model for adoption preferences using Schwarz (Schwarz, 2007) surveyed results on water-saving shower heads for energy-saving feedback technology. This transfer is motivated by the relatively high similarity between these two resource-saving technologies.

These adoption decisions are equivalent to simpler decision rules. First, the lifestyles Postmaterialists and Social Leaders always decide in favor of the environmental-friendly option. Second, the Mainstream and Traditionalist lifestyles are, with an equal probability, randomly choosing between imitating the majority of their peers and adopting the eco-friendly option. Finally, agents of the Hedonistic lifestyle always decide to imitate the majority of their peers.

SUBMODEL: FEEDBACK EFFECT

The sub-model *Feedback Effect* describes how adopted feedback technology changes the agent's heating behavior state variable. We model behavioral change from feedback

technology over time as an asymptotic learning process, see Eq. A.1. Thereby, energy consumption behavior (β_t) asymptotically approaches a behavior suggested by the feedback (β^*_∞) with the rate Δ_β.

$$\beta_t = \beta_{t-1} + (\beta^*_\infty - \beta_{t-1}) \cdot \Delta_\beta \tag{A.1}$$

SUBMODEL: BEHAVIOR DIFFUSION

The sub-model Behavior Diffusion describes how peer behavior influences agent heating behavior, see Eq. A.2. The strength of social influence (s_i) drives a household to approach from its own previous behavior ($\beta_{i,t-1}$) toward the behavior of its peers ($\beta_{j,t-1}$) weighted by the strength of their mutual social relationship (w_{ij}).

$$\beta_{i,t} = \beta_{i,t-1} + s_i \cdot \left(\frac{\sum_{j=1}^{N} w_{ij} \cdot \beta_{j,t-1}}{\sum_{j=1}^{N} w_{ij}} - \beta_{i,t-1} \right) \tag{A.2}$$

B

INPUT DATA

In the following, generation of household agents and their social network from empirical data is presented.

Households For all residential buildings in the case area, heated floor area and estimated heating demand were available from municipal data. Due to privacy protection, the number of residents was not available for individual residential buildings, but for building blocks (i.e. neighborhoods). From this, the number of households per building block was calculated based on the regional average household size of c. 2.12 persons Landesbetrieb Information und Technik Nordrhein-Westfalen (IT.NRW) (2014). These household agents were assigned to residential buildings, so that: (1) to each building is assigned at least one household agent, (2) within each building block, the number of assigned household agents per building are ideally proportional to its heated floor area. Thus, household agents of the same building block had approx. the same heated floor area. Finally, household agents were positioned within the spatial extent of their buildings.

Lifestyles were assigned to household agents based on geo-marketing data. Commercial data by the company Microm® provided the locally dominant lifestyle for all road sections in the case area. Each household agent was assigned a lifestyle by expert judgement, depending to the lifestyle data-points in its spatial proximity.

Social network Social influence between household agents is modeled via a social network. This network was empirically based on a mixed-methods social network analysis Prell (2011); Holstein and Straus (2006) conducted in the City of Bottrop, Germany. It provided data on communication on heating behavior. Interviews were conducted with 23 householders; both inhabitants of one-family dwellings and apartment buildings. Personal relations and relations to actors in the value chain of heating/space heating (i.e. craftspeople, manufacturers) were mapped to social network graphs around the interviewed persons Baedeker et al. (2014). According to these

interviews, family and friends have a high impact on decisions regarding ventilation and heating behavior.

Modeling a social network followed two statistical properties, extracted from these ego-networks: (1) the probability of a social network tie to be within the same neighborhood (p_{NBHD}) and (2) the distribution of network degree, i.e. the number of peer households by which a household is influenced (Jensen et al., 2015, Fig. 3). These data points were complemented by data from Holtzhauer Holzhauer (2015), describing how lifestyle groups are mutually connected in social networks of influence (see Table B.1).

Table B.1: Probability of an influencing peer to be of a specific lifestyle, depending on ego's lifestyle (Holzhauer, 2015, Fig. 3.8).
Note that in this study Traditional Lifestyles are aggregated with (and as) Mainstream Lifestyles.

Peer lifestyle (influencing householder)	Leading Lifestyles	Mainstream Lifestyles	Traditional Lifestyles	Hedonists Lifestyles
Ego lifestyle (influenced householder)				
Leading Lifestyles	0.59	0.10	0.22	0.09
Mainstream Lifestyles	0.50	0.34	0.12	0.04
Traditional Lifestyles	0.36	0.25	0.32	0.07
Hedonists Lifestyles	0.37	0.15	0.32	0.16

Social network generation, inspired by the Watts & Strogatz Watts and Strogatz (1998) algorithm for creating small-world networks, followed these steps:

1. To each household, assign a degree target (deg_i^*), randomly drawn from an empirical distribution (Jensen et al., 2015, Fig. 3).
2. For each household i with less influencing peers than deg_i^*:
   (a) Randomly choose lifestyle of next peer, weighted by probabilities from Table B.1.
   (b) Create directed network edge from random other household who (1) has the chosen lifestyle and (2) is within the same neighborhood (i.e. closer than d_{NBHD}).
3. For each network edge: delete network edge at probability (1 - p_{NBHD}).
4. Repeat step 2 with the altered constraint that new peers are *not* in the same neighborhood (i.e. distance greater than d_{NBHD}).

C

GOOGLE TRENDS

Frequency of Google searches on SV behavior was used as a proxy for frequency of deliberation on its adoption. Google Trends Google (2015) was inquired for the frequency of Google searches for 'Stoßlüften' (i.e. the German term for shock-ventilation). Google Trends is *"a real-time daily and weekly index of the (relative) volume of queries that users enter into Google"* Choi and Varian (2012). Reported sets of data are normalized spatially and temporally by being *"divided by a common variable, like total searches"* Google (2015).

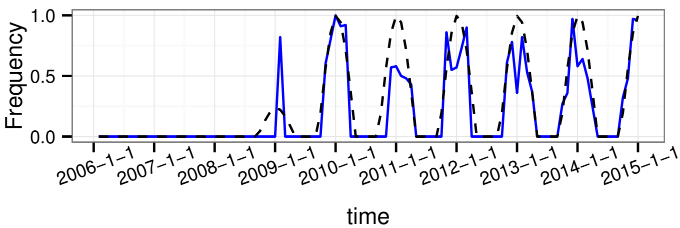

Figure C.1: **Google Trends data and simplified sine curve.** The solid line shows the normalized Google search activity for the German expression for shock-ventilation. The dashed line is fitted to this data (see Eq. C.1) and used in the model.

Search frequency is shown in Fig. C.1. In the Google search frequency two patterns were observed—a seasonal and an inter-annual one. Seasonally, frequency mirrors the relevance of energy-efficient ventilation during winter. Inter-annually, frequency increased after 2009 and reached a plateau.[1] However, the outlying winter of 2010/2011—with relatively low search frequency—could neither be explained by winter temperatures nor press article frequency on SV.

[1] This inter-annual pattern was verified by analyzing all German press articles in the GENIOS.DE database. Articles containing 'Stoßlüften' (normalized by the number of all articles) quickly became more frequent by a factor of c. 2.5 in 2007 and remained at that level.

Table C.1: Survey results on the stated information on and motivation to adopt SV behavior. Listed are relative shares of information/motivation sources. Responses cumulated to n responses, multiple responses being allowed. The two last rows separate the motivation to adoption SV behavior into motivation from information and social influence (see text for details).

Response	**Colleagues & classmates**	**Family & household**	**Friends & acquaintances**	**Mass media**	**∑ %**	**n**
Information on SV	3.8 %	23.2 %	19.6 %	53.6 %	100	56
Motivated SV adoption	5.9 %	35.3 %	17.6 %	41.1 %	100	56
Motivation: *information*	2.7 %	17.8 %	15.1 %	41.2 %	76.9	17
Motivation: *social influence*	3.1 %	17.5 %	2.5 %	0 %	23.1	17

Google search activities were mathematically generalized with Eq. C.1, which distinguishes these two temporal patterns. The function of this equation is shown by the dashed line in Fig. C.1. It is the product of two mathematical terms, which are functions of the time step (i.e. month) of simulation, starting in January 2006: (1) The seasonal peaking of searches on SV during winter motivated using a sine function as a generalization (see Eq. C.2). Similar to the search data pattern, this function peaks during winter (i.e. in January) and does not assume negative values. (2) To also capture the inter-annual pattern, this first term is scaled linearly by Eq. C.3. In the Google Trends data, search activity on SV behavior was absent before the winter of 2008/2009, relatively low during the winter of 2008/2009, and relatively constant thereafter. These three phases are represented by linear factors to the seasonal sine function. Their respective factors represent the difference in the integral over the respective winter peaks in search activity.

$$\delta_{\beta,fit}(t) = \delta_{\beta,annual} \cdot \delta_{\alpha,season} \tag{C.1}$$

$$\delta_{\beta,season}(t) = \max\left[0, \sin\left(\frac{t-2.23}{6} \cdot \pi\right) \cdot 0.72 + (1-0.72)\right] \tag{C.2}$$

$$\delta_{\beta,annual}(t) = \begin{cases} 0 & \text{if } t \leq 30 \\ 0.235 & \text{if } 30 < t < 42 \\ 1 & \text{if } t \geq 42 \end{cases} \tag{C.3}$$

Assuming that search activity is generally proportional to the occurrence of events that trigger deliberation on SV adoption, both these components were scaled by the rate at which such events occur. Both the inter-annual and seasonal patterns of information search activity are thus scaled by the the occurrence rate of events that trigger deliberation on SV adoption ($\delta_{\beta,event}$). Because this rate was not available from the literature, it was parameterized indirectly as ranging from 0.01 to 0.03 (see 4.4.5). Thus, average modeled occurrence of events that can trigger adoption deliberation is between c. 2.5 to 8 years.

$$\delta_{\beta}(t) = \delta_{\beta,event} \cdot \delta_{\beta,annual}(t) \cdot \delta_{\beta,season}(t) \tag{C.4}$$

D

SURVEY EVALUATION

This section presents how shares of SV adoption motivated by information and social influence were extracted from survey results.

The surveyed relative contribution of sources to information and motivating adoption is shown in Table C.1. Regarding distributing information on SV, social contacts and media had about the same importance of 46 and 54%, respectively. Conversely, media slightly exceeded social contacts in importance for motivating behavior change, with 59 over 41%, respectively.

Even though this could suggest that SV adoption is mainly motivated by social influence (rather than from an information source as media), the authors argue that provision of information from peer has to be considered, too. The importance of media (and thus of information) in motivating SV adoption let us to distinguish motivation further between *motivation from information* and *motivation from social influence*.

The differentiation between media and social contacts in motivating SV adoption was therefore transformed into the differentiation between information and social influence. This was undertaken by combining (1) the assumption that media only exceeds information, but not social influence and (2) the relative strength to which media and each peer category provide information (see Table C.1). As a result, 76.9% of adoptions are resulting from exposure to information, and 23.1% from social influence. If the category 'family and household members' is excluded from this calculation—because it partly covers intra-household interactions—, the shares between social influence and information in motivating SV adoption are 8.8 and 92.2%, respectively.

BIBLIOGRAPHY

Aalen, O. O. and Frigessi, A. What can statistics contribute to a causal understanding? *Scandinavian Journal of Statistics*, 34(1):155–168, 2007.

Afman, M. R., Chappin, E. J. L., Jager, W., and Dijkema, G. P. J. Agent-based model of transitions in consumer lighting. In *Proceedings of 3rd World Congress on Social Simulation, Kassel, Germany*, pages 1–2, 2010. URL http://chappin.com/emile/docs/Afman10a.pdf.

Ahrweiler, P. and Gilbert, N. Caffè nero: the evaluation of social simulation. *Journal of Artificial Societies and Social Simulation*, 8(4), 2005.

Ajzen, I. The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 50(2):179–211, 1991. ISSN 0749-5978. doi: 10.1016/0749-5978(91)90020-T. URL http://www.sciencedirect.com/science/article/pii/074959789190020T.

Anderson, K., Lee, S., and Menassa, C. Impact of social network type and structure on modeling normative energy use behavior interventions. *Journal of Computing in Civil Engineering*, 28(1):30–39, 2014. ISSN 0887-3801. doi: 10.1061/(ASCE)CP.1943-5487.0000314. URL http://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CP.1943-5487.0000314.

Araghi, Y., Lee, E. P., and Bollinger, L. A. Informing agent based models with discrete choice analysis: diffusion of solar pv in the netherlands. *Proceedings of Social Simulation Conference 2014*, 2014.

Armitage, C. J. and Christian, J. From attitudes to behaviour: Basic and applied research on the theory of planned behaviour. *Current Psychology*, 22(3):187–195, September 2003. ISSN 0737-8262, 1936-4733. doi: 10.1007/s12144-003-1015-5. URL http://link.springer.com/article/10.1007/s12144-003-1015-5.

Azar, E. and Menassa, C. C. Framework to evaluate energy-saving potential from occupancy interventions in typical commercial buildings in the United States. *Journal of Computing in Civil Engineering*, 28(1):63–78, 2014. ISSN 0887-3801. doi: 10.1061/(ASCE)CP.1943-5487.0000318. URL http://ascelibrary.org/doi/abs/10.1061/%28ASCE%29CP.1943-5487.0000318.

Azar, E. and Menassa, C. C. Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings. *Energy and Buildings*, 97:205–218, 2015.

Baedeker, C. E-mail communication on results of SusLab project on social networks of heating behavior communication., 2014. Date: 2014-5-22.

Baedeker, C., Greiff, K., Grinewitschus, V., Hasselkuß, M., Keyson, D., Knutsson, J., Liedtke, C., Lockton, D., Lovric, T., Morrison, G., et al. Transition through sustainable product and service innovations in sustainable living labs: application of user-centred research methodology within four Living Labs in Northern Europe. In *IST 2014: 5th International conference on Sustainability Transitions*, 2014.

Bagnoli, F., Liò, P., and Sguanci, L. Risk perception in epidemic modeling. *Physical Review E*, 76(6):061904, December 2007. doi: 10.1103/PhysRevE.76.061904. URL http://link.aps.org/doi/10.1103/PhysRevE.76.061904.

Balaras, C. A., Droutsa, K., Dascalaki, E., and Kontoyiannidis, S. Heating energy consumption and resulting environmental impact of European apartment buildings. *Energy and Buildings*, 37(5):429–442, May 2005a. ISSN 0378-7788. doi: 10.1016/j.enbuild.2004.08.003. URL http://www.sciencedirect.com/science/article/pii/S0378778804002464.

Balaras, C. A., Droutsa, K., Dascalaki, E., and Kontoyiannidis, S. Deterioration of European apartment buildings. *Energy and Buildings*, 37(5):515–527, 2005b.

Balaras, C. A., Gaglia, A. G., Georgopoulou, E., Mirasgedis, S., Sarafidis, Y., and Lalas, D. P. European residential buildings and empirical assessment of the Hellenic building stock, energy consumption, emissions and potential energy savings. *Building and Environment*, 42(3):1298–1314, March 2007. ISSN 0360-1323. doi: 10.1016/j.buildenv.2005.11.001. URL http://www.sciencedirect.com/science/article/pii/S0360132305004671.

Bandura, A. and McClelland, D. C. *Social learning theory*. Prentice-Hall Englewood Cliffs, NJ, 1977.

Bass, F. M. A new product growth for model consumer durables. *Management science*, 15(5):215–227, 1969.

Berkhout, P. H. G., Muskens, J. C., and Velthuijsen, J. W. Defining the rebound effect. *Energy policy*, 28(6):425–432, 2000.

Birol, F. World energy outlook. International Energy Agency, 2008.

Bourdieu, P. *Distinction: A social critique of the judgement of taste*. Harvard University Press, 1984.

Briegel, R., Ernst, A., Holzhauer, S., Klemm, S., Krebs, F., and Piñánez, A. M. Social-ecological modelling with LARA: a psychologically well-founded lightweight agent architecture. In *2012 International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting, Leipzig, Germany*, pages 2513–2520, 2012. URL http://ftp.jaist.ac.jp/pub/sourceforge/l/la/lara-framework/fullPaperBriegelEtAl_preprint.pdf.

Burchell, K., Rettie, R., and Roberts, T. Working together to save energy?, June 2014. Report of the Smart Communities project.

Cantono, S. and Silverberg, G. A percolation model of eco-innovation diffusion: the relationship between diffusion, learning economies and subsidies. *Technological Forecasting and Social Change*, 76(4):487–496, 2009.

Caritas. Energy-saving-check program for low income households, 2016. URL http://www.stromspar-check.de/english.html. Available at: http://www.stromspar-check.de/english.html.

Chappin, E. J. L. *Simulating Energy Transitions.* Next Generation Infrastructures Foundation, 2011. ISBN 9789079787302. PhD thesis, Delft University of Technology.

Chappin, E. J. L. and Dijkema, G. P. J. Modeling for transition management. *Available at SSRN 2618413*, 2015.

Chen, J., Taylor, J. E., and Wei, H.-H. Modeling building occupant network energy consumption decision-making: The interplay between network structure and conservation. *Energy and Buildings*, 47:515–524, April 2012. ISSN 0378-7788. doi: 10.1016/j.enbuild.2011.12.026. URL http://www.sciencedirect.com/science/article/pii/S0378778811006414.

Choi, H. and Varian, H. Predicting the present with Google Trends. *Economic Record*, 88 (s1):2–9, 2012. doi: 10.1111/j.1475-4932.2012.00809.x.

Costanza, E., Ramchurn, S. D., and Jennings, N. R. Understanding domestic energy consumption through interactive visualisation: a field study. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pages 216–225. ACM, 2012.

Cozzo, E., Baños, R. A., Meloni, S., and Moreno, Y. Contact-based social contagion in multiplex networks. *Physical Review E*, 88(5):050801, November 2013. doi: 10.1103/PhysRevE.88.050801. URL http://link.aps.org/doi/10.1103/PhysRevE.88.050801.

Dahlstrom, O., Sornes, K., Eriksen, S. T., and Hertwich, E. G. Life cycle assessment of a single-family residence built to either conventional- or passive house standard. *Energy and Buildings*, 54:470–479, November 2012. ISSN 0378-7788. doi: 10.1016/j.enbuild.2012.07.029.

Darby, S. The effectiveness of feedback on energy consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays, 2006*, 2006. URL http://www2.z3controls.com/doc/ECI-Effectiveness-of-Feedback.pdf.

de Holanda, G. M., Ávila, I. M. A., and Martins, R. B. Mapping users' perspectives and outlining social impacts from digitalization of terrestrial TV in Brazil. *Telematics and Informatics*, 25(1):19–35, 2008.

Delft University of Technology. E-quarium - an energy visualization and advice system. http://www.io.tudelft.nl/actueel/congressen-en-symposia/design-for-our-future-13-september-2013/delft-design-labs/applied-labs/e-quarium/, 2014. Accessed: 2014-07-28.

Delre, S. A., Jager, W., Bijmolt, T. H. A., and Janssen, M. A. Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of Business Research*, 60(8):826–835, August 2007. ISSN 0148-2963. doi: 10.1016/j.jbusres.2007.02.002. URL http://www.sciencedirect.com/science/article/pii/S0148296307000392.

Delre, S. A., Jager, W., Bijmolt, T. H. A., and Janssen, M. A. Will it spread or not? the effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, 27(2):267–282, 2010. ISSN 07376782. doi: 10.1111/j.1540-5885.2010.00714.x.

Drogoul, A., Vanbergue, D., and Meurisse, T. Multi-agent based simulation: Where are the agents? In *Multi-agent-based simulation II*, pages 1–15. Springer, 2002.

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., von Stechow, C., Zwickel, T., and Minx, J., editors. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014.

Ekpenyong, U. E., Zhang, J., and Xia, X. Mathematical modelling for the social impact to energy efficiency savings. *Energy and Buildings*, 84:344–351, 2014. URL http://www.sciencedirect.com/science/article/pii/S0378778814006616.

Elsevier. Scopus, 2015. URL http://www.scopus.com. Retrieved 2015-11-27.

Epstein, J. M. *Growing artificial societies: social science from the bottom up*. Brookings Institution Press, 1996.

Epstein, J. M. Why model? *Journal of Artificial Societies and Social Simulation*, 11(4):12, 2008. URL http://jasss.soc.surrey.ac.uk/11/4/12.html.

Ernst, A. Using spatially explicit marketing data to build social simulations. In Smajgl, A. and Barreteau, O., editors, *Empirical Agent-Based Modelling - Challenges and Solutions*, pages 85–103. Springer New York, January 2014. ISBN 978-1-4614-6133-3, 978-1-4614-6134-0. URL http://link.springer.com/chapter/10.1007/978-1-4614-6134-0_5.

European Parliament, Council of the European Union. Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/ec and 2006/32. *Official Journal of the European Union*, 315:1–56, 2012. URL http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2012:315:0001:0056:EN:PDF.

Eurostat. Final energy consumption in households - data sheet code: t2020_rk200. online, 2016. Accessed: 2016-04-28.

Ferro, E., Caroleo, B., Cantamessa, M., and Leo, M. Policy incentives for innovation diffusion: an agent-based simulation. In *Electronic Government and the Information Systems Perspective*, pages 166–173. Springer, 2010.

Festinger, L. *A theory of cognitive dissonance*, volume 2. Stanford University Press, 1962.

Festinger, L. A theory of social comparison processes. *Human relations*, 7(2):117–140, 1954.

Frenken, K. History, state and prospects of evolutionary models of technical change: a review with special emphasis on complexity theory. *The Netherlands: Utrecht University.*, 2004. URL `http://www.narcis.nl/publication/RecordID/oai:library.tue.nl:656114`.

Frenken, K. Technological innovation and complexity theory. *Economics of Innovation and New Technology*, 15(2):137–155, 2006.

Friege, J. and Chappin, E. J. L. Modelling decisions on energy-efficient renovations: A review. *Renewable and Sustainable Energy Reviews*, 39:196–208, 2014.

Funk, S. and Jansen, V. A. A. Interacting epidemics on overlay networks. *Physical Review E*, 81(3):036118, March 2010. doi: 10.1103/PhysRevE.81.036118. URL `http://link.aps.org/doi/10.1103/PhysRevE.81.036118`.

Galán, J. M., Izquierdo, L. R., Izquierdo, S. S., Santos, J. I., Del Olmo, R., López-Paredes, A., and Edmonds, B. Errors and artefacts in agent-based modelling. *Journal of Artificial Societies and Social Simulation*, 12(1):1, 2009.

Galvin, R. Impediments to energy-efficient ventilation of German dwellings: a case study in Aachen. *Energy and Buildings*, 56:32–40, 2013.

Garcia, R. and Jager, W. From the special issue editors: Agent-based modeling of innovation diffusion. *Journal of Product Innovation Management*, 28(2):148–151, 2011.

Gärling, T. and Axhausen, K. W. Introduction: Habitual travel choice. *Transportation*, 30 (1):1–11, 2003.

Geelen, L. M. J., Huijbregts, M. A. J., Ragas, A. M. J., Bretveld, R. W., Jans, H. W. A., van Doorn, W. J., Evertz, S., and van der Zijden, A. Comparing the effectiveness of interventions to improve ventilation behavior in primary schools. *Indoor Air*, 18(5): 416–424, 2008.

Geels, F. W. and Johnson, V. Adoption, upscaling, replication/circulation, and societal embedding: Four theoretical models of technology diffusion applied to biomass district heating systems in Austria (1979-2013). In *Proc. International Sustainability Conference (IST, Helsinki, Finland, 2015)*, 2015.

Ghorbani, A., Bots, P., Dignum, V., and Dijkema, G. Maia: a framework for developing agent-based social simulations. *Journal of Artificial Societies and Social Simulation*, 16(2):9, 2013. URL `http://jasss.soc.surrey.ac.uk/16/2/9.html`.

Gill, Z. M., Tierney, M. J., Pegg, I. M., and Allan, N. Measured energy and water performance of an aspiring low energy/carbon affordable housing site in the UK. *Energy and Buildings*, 43(1):117–125, 2011.

Göckeritz, S., Schultz, P. W., Rendón, T., Cialdini, R. B., Goldstein, N. J., and Griskevicius, V. Descriptive normative beliefs and conservation behavior: The moderating roles of personal involvement and injunctive normative beliefs. *European Journal of Social Psychology*, 40(3):514–523, April 2010. ISSN 1099-0992. doi: 10.1002/ejsp.643. URL `http://onlinelibrary.wiley.com/doi/10.1002/ejsp.643/abstract`.

Goldenberg, J., Libai, B., and Muller, E. The chilling effects of network externalities. *International Journal of Research in Marketing*, 27(1):4–15, 2010. ISSN 01678116. doi: 10.1016/j.ijresmar.2009.06.006.

Google. Google trends help center, 2015. URL `https://support.google.com/trends`. accessed: 2015-4-15.

Granell, C., Gómez, S., and Arenas, A. Dynamical interplay between awareness and epidemic spreading in multiplex networks. *Physical Review Letters*, 111(12):128701, September 2013. doi: 10.1103/PhysRevLett.111.128701. URL `http://link.aps.org/doi/10.1103/PhysRevLett.111.128701`.

Griffiths, M. and Eftekhari, M. Control of CO_2 in a naturally ventilated classroom. *Energy and Buildings*, 40(4):556–560, 2008.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., and Railsback, S. F. The ODD protocol: A review and first update. *Ecological Modelling*, 221(23):2760–2768, 2010. ISSN 03043800 (ISSN). doi: 10.1016/j.ecolmodel.2010.08.019.

Grimm, V. and Railsback, S. F. *Individual-based modeling and ecology*. Princeton University Press, 2013.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H.-H., Weiner, J., Wiegand, T., and DeAngelis, D. L. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *Science*, 310(5750):987–991, 2005.

Grinewitschus, V., Lovric, T., and Rumler, N. Influence of user behavior and home automation on energy consumption. In *Proceedings of the 7th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL13), Coimbra, Portugal*, pages 11–13, 2013.

Grønhøj, A. and Thøgersen, J. Feedback on household electricity consumption: learning and social influence processes. *International Journal of Consumer Studies*, 35(2):138–145, 2011.

Grossmann, K., Bierwirth, A., Bartke, S., Jensen, T., Kabisch, S., von Malottki, C., Mayer, I., and Rugamer, J. Energetic retrofit: considering socio-spatial structures of cities. *GAIA-Ecological Perspectives for Science and Society*, 23(4):309–313, 2014.

Guerra-Santin, O. and Itard, L. Occupants' behaviour: determinants and effects on residential heating consumption. *Building Research & Information*, 38(3):318–338, 2010. URL http://www.tandfonline.com/doi/abs/10.1080/09613211003661074.

Guerra Santin, O., Itard, L., and Visscher, H. The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings*, 41(11):1223–1232, 2009.

Han, Q., Nieuwenhijsen, I., de Vries, B., Blokhuis, E., and Schaefer, W. Intervention strategy to stimulate energy-saving behavior of local residents. *Energy Policy*, 52: 706–715, 2013.

Hansmeier, N. and Matthies, E. Energiebewusste RUB – Richtig Heizen und Lüften. Ergebnisse einer umweltpsychologischen Intervention zur Förderung energieeffizienten Verhaltens an der Ruhr-Universität Bochum. URL http://www.change-energie.de/projekt/download/EnergiebewussteRUB%20_Projektbericht.pdf. Project Report, Ruhr-University Bochum, Faculty for Psychology., 2007.

Hochman Consultants LLC. The cost of pay-per-click (PPC) advertising – trends and analysis, 2016. URL https://www.hochmanconsultants.com/cost-of-ppc-advertising/. Accessed: 2016-09-13.

Holstein, B. and Straus, F. *Qualitative Netzwerkanalyse. Konzepte, Methoden, Anwendungen.* Wiesbaden: Verlag für Sozialwissenschaften, 2006.

Holzhauer, S. *Dynamic Social Networks in Agent-based Modelling - Increasingly Detailed Approaches of Network Initialisation and Network Dynamics.* PhD thesis, University Kassel, 2015. Unpublished.

Holzhauer, S., Krebs, F., and Ernst, A. Considering baseline homophily when generating spatial social networks for agent-based modelling. *Computational and Mathematical Organization Theory*, 19(2):128–150, June 2013. ISSN 1381-298X, 1572-9346. doi: 10.1007/s10588-012-9145-7. URL http://link.springer.com/article/10.1007/s10588-012-9145-7.

Institut für Energie-und Umweltforschung Heidelberg GmbH. Gutachten zur Übertragung des Hamburger Fifty-Fifty-Modells auf ALG II- und Sozialhilfe-Bezieher, 2009.

IPCC. Climate change 2007: synthesis report. *Adopted by Session at IPCC Plenary XXVII*, 2007.

Itard, L. and Meijer, F. *Towards a Sustainable Northern European Housing Stock: Figures, Facts, and Future*, volume 22. Ios Press, 2008.

Jackson, T. *Motivating sustainable consumption: a review of evidence on consumer behaviour and behavioural change: a report to the Sustainable Development Research Network*. Centre for Environmental Strategy, University of Surrey, 2005.

Jager, W. Breaking 'bad habits': a dynamical perspective on habit formation and change. In Hendrickx, L., Jager, W., and Steg, L., editors, *Human Decision Making and Environmental Perception. Understanding and Assisting Human Decision Making in Real-life Settings*. University of Groningen, 2003. URL `http://www.rug.nl/staff/w.jager/jager_habits_chapter_2003.pdf`.

Jager, W. and Janssen, M. An updated conceptual framework for integrated modeling of human decision making: The Consumat II. In *Paper for Workshop Complexity in the Real World@ ECCS*, pages 1–18, 2012. URL `http://www.rug.nl/staff/w.jager/jager_janssen_eccs_2012.pdf`.

Jain, R. K., Gulbinas, R., Taylor, J. E., and Culligan, P. J. Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback. *Energy and Buildings*, 66: 119–127, November 2013. ISSN 0378-7788. doi: 10.1016/j.enbuild.2013.06.029. URL `http://www.sciencedirect.com/science/article/pii/S0378778813003782`.

Jain, R. K. *Building Eco-Informatics: Examining the Dynamics of Eco-Feedback Design and Peer Networks to Achieve Sustainable Reductions in Energy Consumption*. PhD thesis, Columbia University, 2013. URL `http://academiccommons.columbia.edu/catalog/ac:165189`.

Janssen, M. and Jager, W. An integrated approach to simulating behavioural processes: A case study of the lock-in of consumption patterns. *Journal of Artificial Societies and Social Simulation*, 2(2):21–35, 1999. URL `http://jasss.soc.surrey.ac.uk/2/2/2.html`.

Janssen, M. A. and Jager, W. Stimulating diffusion of green products. *Journal of Evolutionary Economics*, 12(3):283–306, 2002. URL `http://link.springer.com/article/10.1007/s00191-002-0120-1`.

Jensen, T. and Chappin, E. J. L. Reducing domestic heating demand: managing the impact of behavior-changing feedback devices via marketing. *Environmental Management*, 2016. Under review.

Jensen, T., Holtz, G., Baedeker, C., and Chappin, E. Energy-efficiency impacts of an air-quality feedback device in residential buildings: an agent-based modeling assessment. *Energy and Buildings*, 116:105–119, 2016.

Jensen, T. and Chappin, E. J. L. Towards an agent-based model on co-diffusion of technology and behavior: a review. In *28th European Conference on Modeling and Simulation 2014, Brescia*, pages 782–788, May 2014.

Jensen, T., Holtz, G., and Chappin, E. J. L. Agent-based assessment framework for behavior-changing feedback devices: spreading of devices and heating behavior.

Technological Forecasting and Social Change, 98:105–119, September 2015. doi: 10.1016/j.techfore.2015.06.006.

Karlin, B., Ford, R., and Squiers, C. Energy feedback technology: a review and taxonomy of products and platforms. *Energy Efficiency*, 7(3):377–399, June 2014. ISSN 1570-646X, 1570-6478. doi: 10.1007/s12053-013-9227-5. URL http://rd.springer.com/article/10.1007/s12053-013-9227-5?no-access=true.

Karlin, B., Zinger, J. F., and Ford, R. The effects of feedback on energy conservation: A meta-analysis. *Psychological bulletin*, 141(6):1205, 2015.

Kelly, K. *What technology wants*. Penguin, 2010.

Kiesling, E., Günther, M., Stummer, C., and Wakolbinger, L. An agent-based simulation model for the market diffusion of a second generation biofuel. In *Proceedings - Winter Simulation Conference*, pages 1474–1481, 2009. ISBN 978-142445770-0. doi: 10.1109/WSC.2009.5429299.

Kiesling, E., Günther, M., Stummer, C., and Wakolbinger, L. M. Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, 20(2):183–230, 2012.

Kroh, J., Ernst, A., Welzer, H., Briegel, R., David, M., Kuhn, S., Piñánez, A. M., Schönborn, S., and Gellrich, A. *Überregionale Potentiale lokaler Innovationsimpulse. Zur Diffusion sozio-technischer Innovationen im Bereich Erneuerbare Energien*, volume 6. Kassel University Press GmbH, 2012. URL http://books.google.de/books?hl=en&lr=&id=CXO_liUYZT0C&oi=fnd&pg=PP1&dq=Potentiale+lokaler+innovationsimpulse&ots=ioxzgroTcv&sig=ZrEiDuY1SKi4sMZWUCfLwyU_ehw.

Landesbetrieb Information und Technik Nordrhein-Westfalen (IT.NRW). Datasheet 'Privathaushalte nach Haushaltsgrößen - Muenster, Regierungsbezirk', 2014. Accessed: 2014-11-07.

Laschke, M., Hassenzahl, M., and Diefenbach, S. Things with attitude: Transformational Products. In *Create11 Conference*, page 1–2, 2011. URL http://create10.squarespace.com/storage/create11paperspostersThings%20with%20attitude.pdf.

Leek, J. T. and Peng, R. D. What is the question? *Science*, 347(6228):1314–1315, 2015.

Lewin, K. Group decision and social change. *Readings in Social Psychology*, 3:197–211, 1947.

Liedtke, C., Hasselkuß, M., Welfens, M. J., Nordmann, J., and Baedeker, C. Transformation towards sustainable consumption: Changing consumption patterns through meaning in social practices. In *4th International Conference on Sustainability Transitions*, pages 702–729, ETH Zurich, Switzerland, June 2013.

Liedtke, C., Baedeker, C., Hasselkuß, M., Rohn, H., and Grinewitschus, V. User-integrated innovation in Sustainable LivingLabs: an experimental infrastructure for researching and developing sustainable product service systems. *Journal of Cleaner Production*, 97:106–116, 2015. ISSN 0959-6526. doi: 10.1016/j.jclepro.2014.04.070. URL http://www.sciencedirect.com/science/article/pii/S0959652614004338.

Loock, C.-M., Staake, T., and Thiesse, F. Motivating energy-efficient behavior with green is: An investigation of goal setting and the role of defaults. *Mis Quarterly*, 37(4): 1313–1332, 2013.

Lopes, M., Antunes, C., and Martins, N. Energy behaviours as promoters of energy efficiency: A 21st century review. *Renewable and Sustainable Energy Reviews*, 16(6): 4095–4104, 2012.

Lovric, T. Unpublished results from living lab experiments in the SusLab project (www.suslab.eu), conducted by the 'University of Applied Sciences Ruhr West', April 2015.

Macal, C. M. and North, M. J. Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3):151–162, 2010.

McCarthy, E. J. *Basic Marketing*, volume 8. McGraw-Hill Education, 1996.

McDonnell, A. *Barriers and Enablers to Energy Efficient Retrofitting of Dwellings in Ireland Masters thesis*. PhD thesis, Waterford Institute of Technology, January 2010.

Mohammadi, N., Wang, Q., and Taylo, J. E. Exploring the potential influence of Opinion Leaders in diffusion of energy conservation practices. In Tolk, A., Diallo, S. Y., Ryzhov, I. O., Yilmaz, L., Buckley, S., and Miller, J. A., editors, *Proceedings of the 2014 Winter Simulation Conference*, 2014.

Nisbet, M. C. and Kotcher, J. E. A two-step flow of influence? Opinion-leader campaigns on climate change. *Science Communication*, 2009.

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., and Griskevicius, V. Normative social influence is underdetected. *Personality and Social Psychology Bulletin*, 34(7): 913–923, January 2008. ISSN 0146-1672, 1552-7433. doi: 10.1177/0146167208316691. URL http://psp.sagepub.com/content/34/7/913.

North, M. J., Collier, N. T., Ozik, J., Tatara, E. R., Macal, C. M., Bragen, M., and Sydelko, P. Complex adaptive systems modeling with Repast Simphony. *Complex adaptive systems modeling*, 1(1):1–26, 2013.

Olivier, J. G., Janssens-Maenhout, G., Marilena, M., and Peters, J. A. Trends in global CO_2 emissions: 2015 report, 2015. URL http://edgar.jrc.ec.europa.eu/news_docs/jrc-2015-trends-in-global-co2-emissions-2015-report-98184.pdf.

Oxford University Press. Policy, 2016. URL http://www.oxforddictionaries.com/definition/english/policy. Accessed: 2016-04-22.

Padonou, E., Villot, J., et al. Estimation of energy savings through a kriging metamodel. *ENBIS-13 Summary Session Reports, 2013.*, 2013.

Pentland, A. *Social physics. How good ideas spread - the lessons from a new science.* Penguin Books Ltd, 2014.

Pérez-Lombard, L., Ortiz, J., and Pout, C. A review on buildings energy consumption information. *Energy and buildings*, 40(3):394–398, 2008.

Peschiera, G., Taylor, J. E., and Siegel, J. A. Response-relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data. *Energy and Buildings*, 42(8):1329–1336, August 2010. ISSN 0378-7788. doi: 10.1016/j.enbuild.2010.03.001. URL `http://www.sciencedirect.com/science/article/pii/S0378778810000691`.

Piacentini, J., Woods, D. W., Scahill, L., Wilhelm, S., Peterson, A. L., Chang, S., Ginsburg, G. S., Deckersbach, T., Dziura, J., and Levi-Pearl, S. Behavior therapy for children with tourette disorder: a randomized controlled trial. *Jama*, 303(19):1929–1937, 2010. URL `http://archinte.jamanetwork.com/article.aspx?articleid=185896`.

Prell, C. *Social network analysis: History, theory and methodology.* Sage, 2011.

Provost, F. and Fawcett, T. *Data Science for Business: What you need to know about data mining and data-analytic thinking.* " O'Reilly Media, Inc.", 2013.

Railsback, S. F. and Grimm, V. *Agent-Based and Individual-Based Modeling: A Practical Introduction.* Princeton University Press, October 2011. ISBN 1400840651.

Rand, W. and Rust, R. Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, 28(3):181–193, 2011. ISSN 01678116. doi: 10.1016/j.ijresmar.2011.04.002.

Rixen, M. and Weigand, J. Agent-based simulation of policy induced diffusion of smart meters. *Technological Forecasting and Social Change*, 85:153–167, 2014.

Rogers, E. M. *Diffusion of Innovations.* Simon and Schuster, 2010.

Rogers, E. M. *Diffusion of Innovation.* Free Press, New York, 5 edition, 2003.

Roozenburg, N. F. M. and Eekels, J. *Product Design: Fundamentals and Methods.* John Wiles & Sons, 1995.

Santamouris, M., Synnefa, A., Asssimakopoulos, M., Livada, I., Pavlou, K., Papaglastra, M., Gaitani, N., Kolokotsa, D., and Assimakopoulos, V. Experimental investigation of the air flow and indoor carbon dioxide concentration in classrooms with intermittent natural ventilation. *Energy and Buildings*, 40(10):1833–1843, 2008.

Schreinemachers, P., Berger, T., and Aune, J. B. Simulating soil fertility and poverty dynamics in Uganda: A bio-economic multi-agent systems approach. *Ecological Economics*, 64(2):387–401, 2007.

Schwarz, N. and Ernst, A. Agent-based modeling of the diffusion of environmental innovations - an empirical approach. *Technological Forecasting and Social Change*, 76(4):497–511, 2009. ISSN 00401625. doi: 10.1016/j.techfore.2008.03.024.

Schwarz, N. *Umweltinnovationen und Lebensstile: eine raumbezogene, empirisch fundierte Multi-Agenten-Simulation.* PhD thesis, Metropolis-Verl., Marburg, 2007.

Shipworth, M., Firth, S. K., Gentry, M. I., Wright, A. J., Shipworth, D. T., and Lomas, K. J. Central heating thermostat settings and timing: building demographics. *Building Research & Information*, 38(1):50–69, 2010.

Sinus Sociovision. Sinus-Milieus, 2015. URL http://www.sinus-sociovision.de/en/.

Sonnessa, M. Modelling and simulation of complex systems. *PhD thesis, University of Torino, Italy*, 2004.

Sopha, B. M., Klöckner, C. A., and Hertwich, E. G. Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. *Energy Policy*, 39(5):2722–2729, May 2011. ISSN 03014215. doi: 10.1016/j.enpol.2011.02.041. URL http://linkinghub.elsevier.com/retrieve/pii/S0301421511001315.

Sopha, B. M., Klöckner, C. A., and Hertwich, E. G. Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions*, 8:42–61, September 2013. ISSN 2210-4224. doi: 10.1016/j.eist.2013.06.001. URL http://www.sciencedirect.com/science/article/pii/S2210422413000427.

Stern, N. Economics: Current climate models are grossly misleading. *Nature*, 530(7591): 407, 2016.

Stonedahl, F. and Wilensky, U. BehaviorSearch, 2016. URL http://behaviorsearch.org. Accessed: 2016-04-21.

Strasak, A. M., Zaman, Q., Pfeiffer, K. P., Gobel, G., and Ulmer, H. Statistical errors in medical research-a review of common pitfalls. *Swiss medical weekly*, 137(3/4):44, 2007.

Stromback, J., Dromacque, C., and Yassin, M. H. The potential of smart meter enabled programs to increase energy and systems efficiency: a mass pilot comparison, 2011. URL http://esmig.eu/sites/default/files/2011.10.12_empower_demand_report_final.pdf.

Thaler, R. H. and Sunstein, C. R. *Nudge: Improving decisions about health, wealth and happiness.* Penguin Books Ltd, 2009.

Thiele, J. C. and Grimm, V. Replicating and breaking models: good for you and good for ecology. *Oikos*, 2015.

Tisue, S. and Wilensky, U. Netlogo: A simple environment for modeling complexity. In *International Conference on Complex Systems*, pages 16–21, 2004.

Tukker, A., Cohen, M. J., Hubacek, K., and Mont, O. The impacts of household consumption and options for change. *Journal of Industrial Ecology*, 14(1):13–30, 2010.

van Dam, K. H., Nikolic, I., and Lukszo, Z. *Agent-Based Modelling of Socio-Technical Systems*. Springer, Guildford and UK, 2012.

Van Eck, P., Jager, W., and Leeflang, P. Opinion Leaders' role in innovation diffusion: A simulation study. *Journal of Product Innovation Management*, 28(2):187–203, 2011. ISSN 07376782. doi: 10.1111/j.1540-5885.2011.00791.x.

Verplanken, B. and Wood, W. Interventions to break and create consumer habits. *Journal of Public Policy & Marketing*, 25(1):90–103, 2006. URL http://journals.ama.org/doi/abs/10.1509/jppm.25.1.90.

Watts, C. and Gilbert, N. *Simulating Innovation: Computer-based Tools for Rethinking Innovation*. Edward Elgar Publishing, 2014.

Watts, D. J. and Strogatz, S. H. Collective dynamics of 'small-world' networks. *Nature*, 393(6684):440–442, 1998.

Wiegand, T., Jeltsch, F., Hanski, I., and Grimm, V. Using pattern-oriented modeling for revealing hidden information: a key for reconciling ecological theory and application. *Oikos*, 100(2):209–222, 2003.

Wilhite, H., Nakagami, H., Masuda, T., Yamaga, Y., and Haneda, H. A cross-cultural analysis of household energy use behaviour in Japan and Norway. *Energy Policy*, 24 (9):795–803, 1996.

Windrum, P., Moneta, A., and Fagiolo, G. Empirical validation of agent-based models: Alternatives and prospects, March 2007. URL http://jasss.soc.surrey.ac.uk/10/2/8.html.

Wood, G. and Newborough, M. Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings*, 35(8):821–841, September 2003. ISSN 03787788. doi: 10.1016/S0378-7788(02)00241-4. URL http://linkinghub.elsevier.com/retrieve/pii/S0378778802002414.

Zhang, H., Vorobeychik, Y., Letchford, J., and Lakkaraju, K. Data-driven agent-based modeling, with application to rooftop solar adoption. In *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*, pages 513–521. International Foundation for Autonomous Agents and Multiagent Systems, 2015.

Zhang, T., Siebers, P.-O., and Aickelin, U. Modelling electricity consumption in office buildings: An agent based approach. *Energy and Buildings*, 43(10):2882–2892, 2011. ISSN 03787788. doi: 10.1016/j.enbuild.2011.07.007.

Zhang, T. and Nuttall, W. J. Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation. *Journal of Product Innovation Management*, 28(2):169–186, 2011. ISSN 1540-5885. doi: 10.1111/j.1540-5885.2011.00790.x.

Zhang, T. and Nuttall, W. J. An agent-based simulation of Smart Metering technology adoption. *International Journal of Agent Technologies and Systems*, 4(1):17–38, 2012. ISSN 1943-0744, 1943-0752. doi: 10.4018/jats.2012010102. URL `http://www.igi-global.com/article/content/66067`.

Curriculum Vitæ

Thorben Jensen was born on September 1, 1987 in Langenhagen, Germany. After completing high school education at Gymnasium Langenhagen in 2007, he enrolled at Osnabrück University (Germany) for the Bachelor of Science program Applied Systems Science, with the minor subjects of computer science, mathematics, geography, and geomatics. During his studies, he spent a semester studying mathematics at the University of Granada (Spain). He graduated from his B.Sc. program in 2011. His Bachelor's thesis focused on simulating the transport and fate of medicinal compounds in the environment. He continued his studies with the Master of Science program Environmental Systems and Resource Management, with the minor subjects of computer science and geomatics. During the M.Sc. program he took part in courses on simulation modeling and resource management at the 'Institute for life, food and horticultural sciences and landscaping' in Angers (France) and at the University Center in Svalbard (Spitsbergen). Additionally, he assisted at teaching several classes at Osnabrück University and became a research assistant at the Helmholtz Centers for Environmental Research and for Polar and Marine research. In 2013, he graduated from his M.Sc. program. In his graduation project, he simulated the storage of CO_2 in the Arctic Ocean under a changing climate.

In the year 2013, he became a PhD candidate in the section Energy and Industry at the Faculty of Technology, Policy and Management, at Delft University of Technology. In the same year, he took up a position as a Research Fellow at Wuppertal Institute for Climate, Environment, and Energy (Germany) and was a guest lecturer on data analysis at University of Angers (France). In his PhD project, he drew on his interest in computer science. In his daily work, he enjoyed automating routine tasks, which eventually led him to his contribution of automating major parts of model generation and policy assessment for innovation diffusion models.

During his PhD he made use of many traveling opportunities. In 2015, a scholarship sponsored by the foundations Robert Bosch and Mercator allowed him to be a visiting researcher at the Chinese 'Green Development Low-carbon Think Tank Partnership'. He presented at several conferences—in China, the US, and Europe. In France, his work on automated model generation was awarded with the 'Best Student Paper Prize' by the International Environmental Modeling and Software Society.

At the time of writing, he continues to explore data driven modeling as a Data Scientist at EY (Ernst & Young).

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Publications by author

1. Jensen, T. and Chappin, E. J. L. *Towards an agent-based model on co-diffusion of technology and behavior: a review*, proceedings of the 28th European Conference on Modelling and Simulation, Brescia, Italy, 782–788, 2014.

2. Großmann, K., Bierwirth, A., Bartke, S., Jensen, T., Kabisch, S., Malottki, C. v., Mayer, I., and Rügamer, J., *Energetic retrofit: considering socio-spatial structures of cities*, GAIA-Ecological Perspectives for Science and Society **23 (4)**, 309-312 (2014).

3. Jensen, T., Holtz, G., and Chappin E. J. L. *Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior*, Technological Forecasting and Social Change **98**, 105–119, 2015.

4. Holtz, G., Jensen, T., and Chappin, E. J. L. *Modelling the diffusion and effect of behavior changing feedback devices*, proceedings of the 2015 Annual Conference of the EU-SPRI Forum, 2015.

5. Jensen, T., Holtz, G., Baedeker, C., and Chappin, E. J. L. *Energy-efficiency impacts of an air-quality feedback device in residential buildings: an agent-based modeling assessment*, Energy and Buildings **116**, 151–163, 2016.[1]

6. Jensen, T. and Chappin, E. J. L. *Agent-based modeling automated: data-driven generation of innovation diffusion models*, proceedings of the 8th International Congress on Environmental Modelling and Software, Toulouse, France, 2016.[2]

7. Jensen, T. *Agent-based modeling 2.0: automated generation of innovation diffusion models*, poster presented at the 5th International Engineering Systems Symposium, Washington, D.C., USA, 2016.

8. Jensen, T. *Reducing domestic heating demand: managing the impact of behavior-changing feedback devices via marketing*, Environmental Management, under review, 2016.

9. Jensen, T., Holtz, G., and Chappin, E. J. L. *Automated model structure variation and policy robustness testing: a procedure for innovation diffusion models*, proceedings of the Social Simulation Conference, Rome, Italy, 2016.

10. Jensen, T. and Chappin, E. J. L. *Automating agent-based modeling: data-driven generation and application of innovation diffusion models*, Environmental Modeling and Software, in press, 2017.

[1] This contribution has been selected as one of the ten most important scientific publications of the Wuppertal Institute in 2016.

[2] This contribution has been awarded with the 'Best Student Paper Prize' by the International Environmental Modeling and Software Society.