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Digitalization, business models, and SMEs: How do business model innovation practices improve performance of digitalizing SMEs?

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ABSTRACT

Digital transformation is requiring companies to rethink and innovate their business models (BMs). However, small- and medium-sized enterprises (SMEs) have scarce time and resources for experimenting with their BMs and implementing new strategies. This paper examines whether SMEs that undergo digital transformation perform better if they allocate more resources for BM experimentation and engage more in strategy implementation. An empirical study was conducted on 321 European SMEs that actively use social media, big data, and information technology to innovate their BMs. Furthermore, structural equation modelling showed positive overall firm performance effects of more resource allocation to BM experimentation and more engagement in practices of strategy implementation. These effects were mediated by BM experimentation practices and company innovativeness. Moreover, fuzzy-set qualitative comparative analysis (fsQCA) revealed the presence of equifinality by identifying different configurations in which these antecedent conditions affect overall firm overall performance. The results of two methodological approaches showed that SMEs may take different routes to improve their performance when digital transformation is changing their BM. This paper is one of the first to analyse how SMEs can handle the impact of digitalization by spending more time and effort on innovating their BMs. Practical and policy implications are discussed.

1. Introduction

Digital transformation is changing how small- and medium-sized enterprises (SMEs) create and capture value (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Lucas, Agarwal, Clemons, El Sawy, & Weber, 2013). Digital transformation is defined as the process that is used to restructure economies, institutions, and society on a system level (Unruh & Kiron, 2017). For instance, social media are changing how companies interact with customers, deliver their services, and integrate their IT systems. Big data is not only relevant for marketing and customer relationship management, but also for new data-driven revenue models and preventive maintenance. Digital transformation is not about optimizing internal processes or incorporating new technologies, but fundamentally changing SMEs' business models (Loebbecke & Picot, 2015). Therefore, strategic decisions on digital transformation do not automatically improve performance, because it requires SMEs to rethink and change their business model (hereinafter BM).

Although some authors hold the opinion that the BM concept is poorly defined and misunderstood (Teece, 2010), we view it as the way companies create and capture value for their customers and for themselves. In our more extensive definition, a BM refers to the way a single organization or a network of organizations collaborates at strategic and operational levels to offer and exploit products

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and/or services (bundles). In order to do so, a single organization or a network of firms can make use of platforms, IT architectures, and applications (Bouwman, Haaker, & De Vos, 2008). Moreover, attention to business model innovation (hereinafter BMI) is increasing both in practice and in research (Lambert & Davidson, 2013; Wirtz, Göttel, & Daiser, 2016; Zott & Amit, 2010). BMI is defined as a change in a company's BM architecture or its components (Foss & Saebi, 2017) that is new to the firm and results in observable changes in the company's practices towards customers and partners. BMI takes place through a learning process in which discovery via experimentation is more appropriate than conventional analytical approaches (McGrath, 2010) or more cognitive-oriented approaches (Berends, Smits, Reymen, & Podoynitsyna, 2016; Martins, Rindova, & Greenbaum, 2015; Tikkanen, Lamberg, Parvinen, & Kallunki, 2005). In BM experimentation, alternative BMs or configurations of BM components are examined using either thought (virtual) or real-life experiments (Baden-Fuller & Morgan, 2010). This requires resources—companies' time and effort—-which are especially scarce in most SMEs (Heikkilä, Bouwman, & Heikkilä, 2018). Therefore, a concern is whether spending time and resources on BM experimentation actually contributes to firms' overall performance.

The large number of new opportunities driven by digitalization put pressure on SMEs to reconsider their current BMs or critically reflect on their current strategy in order to identify new business opportunities (Kiel, Arnold, Collisi, & Voigt, 2016, p. 675). Wirtz, Schilke, and Ullrich (2010, p. 273) suggested that managers may require to adapt one or more aspects of their BMs or even design completely new ones. The focus of our research is specifically on SMEs experimenting with BMs as a result of the strategic decision to introduce social media, big data, and/or information technology as instantiations of digital transformation (Rachinger, Rauter, Mu¨ller, Vorraber, & Schirgi, 2018). We follow the view proposed by Al-Debei and Avison (2010) in which BMs are conceptualized as ways to implement strategic decisions. BM strategy implementation practices are defined as the activities and ways of working of a team in charge of an experimentation process. In order to realize a BM innovation, resources have to be allocated; therefore, we focus on resources for BM experimentation as an explanatory factor. These resources are committed for assigning BM experimentation tasks to a specific manager or a team.

The goal of this paper is to examine whether SMEs that undertake digital transformation perform better if they allocate more resources for BM experimentation and engage more in strategy implementation. Based on a survey, a dataset of 321 European SMEs from 12 countries engaged in BMI related to social media and big data was analysed. This dataset is a subset of a larger sample of companies engaged in BMI (N = 563). Data were collected in 2017. We used a mixed methods approach with the purpose of expansion (Venkatesh, Brown, & Bala, 2013, p. 26 p. 26)—we used a quantitative method (i.e., PLS-SEM) to test hypotheses and a configurational qualitative thinking method (i.e., fuzzy-set qualitative comparative analysis [fsQCA]; Ragin, 1987) to examine causal complexity. The advantage of using PLS-SEM is that it provides a commonly accepted statistical approach for testing hypotheses in a generalizable way. The fsQCA method compensates for two weaknesses in the structural equation modelling (SEM) approach: (a) in contrast to regression analysis that assess the net effects of antecedents, fsQCA allows uncovering how combinations of causal measures lead to the outcome of interest (i.e., causal complexity), (b) as regression-based analyses can only uncover necessary conditions that are linearly related to the outcome variable of interest, fsQCA allows a finer grained understanding of the causal mechanisms by adopting a complex causality perspective. Hence, this paper contributes to BMI literature not only by focusing on digital transformation, BMI practices, and SMEs, but also by examining whether there can be different pathways to the same outcome (i.e., improved firm performance in this study). Our study also provides new knowledge to business managers to better understand how firms experiment with BMI and how strategy implementation in a business' logic might affect BMI performance.

The following section reviews empirical literature on BM, BMI, and BM experimentation, innovativeness and performance. In Section 3, research hypotheses are developed. Section 4 discusses the research methodology, data collection process, and the development of measures. Structural equation modelling results are presented in Section 5 and fuzzy-set qualitative comparative analysis, in Section 6. Section 7 presents the discussion and Section 8 outlines this research's theoretical contribution, conclusions, limitations, and considerations for future work.

2. Literature review

Recent papers provide overviews of BM literature (Foss & Saebi, 2017; Lambert & Davidson, 2013; Zott, Amit, & Massa, 2011) and research agenda on BMI (George & Bock, 2011; Veit et al., 2014; Wirtz et al., 2016). We will not repeat those overviews here, but rather review the empirical studies that link BMI, BM experimentation, strategy implementation, and business performance.

2.1. Definitions

Traditionally, BM research has been conducted within three areas: (a) Internet, mobile, and information technologies as they impact businesses at the infrastructure and application levels redefining the role of actors in the converging telecommunications and information systems domain (Ballon, 2007; Bouwman et al., 2008; Methlie & Pedersen, 2007; Walravens, 2015); (b) strategic issues related to firms' performance and value creation (Casadesus-Masanell & Ricart, 2010; Hedman & Kalling, 2003; Zott & Amit, 2008, 2010); and (c) innovation and technology management (Chesbrough, 2006, 2010; Waldner, Poetz, Grimpe, & Eurich, 2015; Zott et al., 2011). BM research is largely based on case studies, specifically in the domain of Internet, mobile communications, Internet-of-Things, cloud computing, and information technologies (Al-Debei, Al-Lozi, & Al-Hurjan, 2015; Ballon, 2007; Bouwman et al., 2008; Dijkman, Sprenkels, Peeters, & Janssen, 2015; Khanagha, Volberda, & Oshri, 2014; Turber, vom Brocke, Gassmann, & Fleisch, 2014).

When reviewing quantitative studies on BMI and performance (e.g., Aspara, Hietanen, & Tikkanen, 2010; Aziz & Mahmood, 2011;

Clausen & Rasmussen, 2013; Huang, Lai, Kao, & Chen, 2012), it is a challenge that studies often lack clear definitions of BM and BMI (Foss & Saebi, 2017). On the one hand, the literature, especially from the digital transformation domain, provides extensive ontologies comprising BM components such as CANVAS (Osterwalder, Pigneur, & Tucci, 2005), C-SOFT/STOF (Bouwman et al., 2008; Heikkilä & Heikkilä, 2013), and VISOR (El Sawy & Pereira, 2013). On the other hand, many quantitative studies on BMI do not relate their core concepts or BM characteristics to these ontologies (e.g., Hartmann, Zaki, Feldmann, & Neely, 2016; Souto, 2015).

We agree with Wirtz et al. (2016) that BMI entails a crucial transformation of a company's existing value proposition and/or value constellation. Some authors such as Bonakdar (2015); Bucherer, Eisert, and Gassmann (2012); Frankenberger, Weiblen, Csik, and Gassmann (2013); and Hartmann et al. (2016) also followed this view and defined BMI as the deliberate modification of one or more core BM components, or the introduction of new components. Björkdahl and Magnus (2013) pointed out that BMI can be the result of novel combinations of new and old products or services, as well as changes in the firm's market position and process management. Lindgardt, Reeves, Stalk, and Deimler (2009) focused on value delivery and defined BMI as the reinvention of two or more BM components that can lead to novel ways of value delivery. The definition of Zott and Amit (2011) suggests that BMI can be the adoption of novel activities that define the BM of a firm, the adoption of new linkages between existing activities, or the replacement of business actors in the firm's value network.

Existing quantitative studies also use various instruments to measure BMI. Velu (2016) considers diversification/product launch and external funding as two indicators of BMI. Others have used dummy variables for consulting BMs, technology BMs, and software BMs (e.g., Clausen & Rasmussen, 2013). Kim and Min (2015) defined BMI simply as adding online retail services. Souto (2015) used an unspecified two-item scale. Huang et al. (2012) used a list of components as indicators. Recently, Clauss (2017) and Spieth and Schneider (2016) made valuable contributions in the form of validated scales to measure BMI.

Research on BM experimentation is scarce. Through an extensive case study, Sosna, Trevinyo-Rodriguez, and Velamuri (2010) found that the exploration phase of BMI consists of initial designs and trial-and-error improvements, which may last for several years before leading to sustained change in the BM. Cavalcante (2013) distinguishes experimentation from learning, defining BM experimentation as researching technical challenges and performing new practices, and BM learning as acquiring new knowledge, discussing new ideas, and contacting and interacting with others, for example, new business partners. Achtenhagen, Melin, and Naldi (2013) concluded, through inductive research, that BM experimentation comprises three activities: (a) retrieving information about the environment, (b) encouraging new ideas, and (c) learning from mistakes. Berends et al. (2016) defined four elements of BMI: (a) conceptualizing new ideas, (b) creating new BMs, (c) adapting the BM after it is in operation, and (d) experimenting to learn about and validate the model. While some of these conceptualizations are congruent, considerable differences emerge as well. For instance, Cavalcante (2013) sees experimentation and learning as different activities, while Berends et al. (2016) define experimentation as learning from experience. In addition, the activities that are part of BMI and experimentation differ between the cited studies. Also, some studies appear to assume that companies pass through experimentation activities sequentially, while others assume an iterative or parallel process.

2.2. Practices of BMI

Overall, most BM experimentation studies develop descriptive process theories rather than explanatory variance theories. Consequently, what role BM experimentation practices play in BMI and how BM experimentation affects organizations' performance and innovativeness is still under-researched. This statement also holds for BM experimentation and digital transformation, for example in relation to social media and big data.

Regarding practices of BMI in general, there is an important link to strategy. The relationship between BMs and strategy has long been debated (Hedman & Kalling, 2003; Seddon, Lewis, Freeman, & Shanks, 2004). Although most scholars agree that BMI and strategy are in some way related, there is less agreement on their exact interrelation (Casadesus-Masanell & Ricart, 2010, Casadesus-Masanell & Zhu, 2013; Chesbrough, 2010; Hedman & Kalling, 2003). Most scholars argue that BMs should be a strategy implementation (Al-Debei & Avison, 2010; Cortimiglia, Ghezzi, & Frank, 2016). Cucculelli and Bettinelli (2015) argued that BMI should be a function of corporate strategic entrepreneurship. For instance, Osterwalder et al. (2005) established a direct link between the concepts of customer intimacy, operational excellence, and product leadership. Another example comes from research by Markides and Sosa (2013), who compared market entrance strategy and BMs. Some scholars argue that strategy is a plan whilst BM is the actual state (e.g., Dahan, Doh, Oetzel, & Yaziji, 2010). In a similar vein, Casadesus-Mansel and Ricart (2010) defined strategy as the contingent plan in which a BM is to be used, whereas a BM is the company's implemented strategy. Consistent with this view of BMs as snapshot materializations of a strategy, a change in strategy will trigger BM experimentation. Through this reasoning, a change of strategy directly implies that the company's BM may have to be changed. In that sense, experimentation is an intermediate step towards realizing a new BM that is in line with a firm's new strategy (Hayashi, 2009; McGrath, 2010; Sosna et al., 2010).

2.3. BMI and SMEs

The few papers that discuss BMI practices focus mainly on large companies (Chesbrough, 2010; Chesbrough & Rosenbloom, 2002; Dunford, Palmer, & Benveniste, 2010). Focusing on SMEs has its complications since SMEs are diverse in nature with regard to industry, size, phase of maturity, and ownership (e.g., family, female entrepreneurship (European Commission, 2017)). SMEs are considered the driving force in most economies, responsible for employment, innovation, and growth, as often argued by the

Organization for Economic Co-Operation and Development (OECD), the European Union, and national governments (see e.g., EASME, 2015) and the European Semester.[1] Although policy changes have been made towards promoting digitalization with a focus on security and high-tech emerging technologies,[2] programs on BMI and digitalization specifically for SMEs are rather traditionally focussed on e-Business as expressed in the Europe 2020 program.[3]

2.4. BMI and innovativeness

Literature on BMI with a focus on SMEs is limited and mainly qualitative in nature (Heikkilä et al., 2018), with a lack of studies that focus on how digitalization affects SMEs' BMs. Moreover, extant quantitative studies are mainly related to the strategic and innovation management domain. From the handful of studies focusing on the impact of digitalization on SMEs, Gruber (2018) has recently identified four reasons to explain why digital transformation is taking place slowly in SMEs. First, small companies with their specific foci are less exposed to the need for rapid digitalization. Second, small companies often lack resources and managerial vision to fully understand the impacts of digital transformation. Third, SMEs usually adopt a gradual approach to digitalization compared to larger companies. Finally, digitalization investment within this type of companies heavily relies on firms' financial performance and it is often the case that they have limited resources to use on this area.

Moreover, innovativeness is a multidimensional concept (Lee & O'Connor, 2003; Siguaw, Simpson & Enz, 2006). Literature suggests two main dimensions. On the one hand, there is a dimension related to the orientation, tendency or culture of the firm. Regarding this dimension, innovativeness refers to the 'openness to new ideas as an aspect of firm's culture' (Hurley & Hult, 1998). On the other hand, there is a dimension related to the capacity of organizations to act in innovative ways. This dimension relates to the 'capacity to engage in innovation or to introduce some new process, product or idea in the organization' (Hult, Hurley, & Knight, 2004). The cultural dimension to innovativeness is often considered as a required condition for the capacity dimension (Bock, Opsahl, George & Gann, 2012; Teece, 2010).

Innovativeness is often conceptualized as an enduring organizational trait (Subramanian & Nilakanta, 1996). Yet, other scholars suggest that innovativeness can be modelled either as a cause or consequence of innovation (Garcia & Calantone, 2002). In the area of BMI, it has been found that reconfiguring a BM provides the capabilities to firms to adopt innovations that were previously not feasible (Siguaw et al., 2006). To give a practical example, Netflix' reconfiguration from a DVD-delivery service to an on-demand subscription service has enabled that firm to adopt innovations regarding data analytics (e.g., recommendation service) and content production processes (e.g., high-budget TV production) which would not have been feasible to adopt with their old BM. There has been support for this assertion, for instance a study showing that using parallel BMs at the same time improve the innovativeness of SMEs (Clausen & Rasmussen, 2013).

2.5. Methods in BMI research

Moreover, some empirical studies show limitations such as the use of secondary data collected for other purposes (Barjak, Es-Sadki, & Arundel, 2014; Cucculelli & Bettinelli, 2015; Hartmann et al., 2016; Kim & Min, 2015). Original data are seldom collected (see e.g., Aspara et al., 2010; Gronum, Steen, & Verreynne, 2015; Zott & Amit, 2008). Furthermore, empirical studies are diverse in their research foci and are based on diverse strategic management perspectives and mainly on linear econometric data analysis (e.g., Cucculelli & Bettinelli, 2015; Hartmann et al., 2016; Kim & Min, 2015; Zott & Amit, 2007). Performance is often the key dependent variable, while linear regression analyses and structural equation modelling (SEM) are the analysis methods most frequently used. It can be concluded that research on BMI is still rather generic and sometimes lacks depth in its understanding of what companies try to achieve when strategic decisions are implemented in the existing business logic.

3. Hypothesis development

As discussed in Section 2, existing quantitative literature that links BM experimentation and strategy implementation practices to firm performance is largely lacking, as is literature on BMI practices. Studies that do relate BMI to firm performance mainly focus on the implications of specific design choices in BMs (e.g., Zott & Amit, 2010) rather than on the process of developing a BM. BM experimentation literature, on the other hand, focuses largely on descriptive process theory and does not typically make assertions about performance implications. Thus, developing hypotheses on how the practices of BMI affect performance is not a straightforward endeavour.

Our main theorization is that spending time and resources on BM experimentation and strategy implementation has a positive effect on the firm performance. Our rationale is that, for firms that are changing their BMs due to digitalization, it pays off to spend time and effort on carefully rethinking and experimenting with new BMs. The core constructs in this theorization are resources and practices. By resources, we refer to budgets, human resources, and time that companies spend on supporting BMI practices. By practices, we refer to the activities carried out within the firm for BMI, such as trying out new BMs, conducting analyses on what has to be changed in a BM, or changing one or more BM components. In line with the literature on BM experimentation and BM strategy,

[1] http://ec.europa.eu/europe2020/targets/eu-targets.
[2] https://ec.europa.eu/digital-single-market/en/news/eu-budget-future-digital-transformation.
[3] https://europa.eu/newsroom/events/fostering-smes-growth-through-digital-transformation_en.

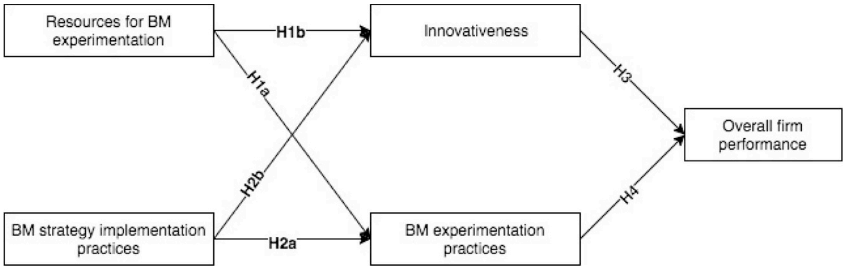

Fig. 1. Research conceptual model.

we distinguish between practices aimed at experimenting with new BMs (e.g., changing a BM component such as the value proposition) and practices aimed at implementing a new strategy into the BM (e.g., deriving changes in the BM from the company strategy).

Our overall leading theoretical model (see Fig. 1) posits that both resources for BM experimentations and for BM strategy implementation practices directly influence business experimentation practices. This means that the more resources become available, the more a company will start activities to change its BM. This paper proposes that BM experimentation practices—discussing and trying out changes in BMs—positively influence the overall firm performance. In what follows, we elaborate further on the constructs discussed above and formulate our research hypotheses.

3.1. Resources for BM experimentation

Resources for BM experimentation entail budgets, human capabilities, and time that a company provides to support BM experimentation practices. BM experimentation practices are activities within the firm related to exploring (a) how to change the company's business logic, that is, incrementally or radically, (b) the order in which changes in components are made, and (c) thought (virtual) versus real experiments. These activities may take place, for instance, in a BM team within a company, as part of the ongoing tasks of managers, or by hiring external advisors based on a budget. We assume that dedicating resources to a specific task enables increased activity on that task. We therefore hypothesize:

H1a. Resource allocation for BM experimentation has a direct effect on BM experimentation practices.

We also posit that allocating resources for BM experimentation contributes directly to the broader concept of *innovativeness* as an outcome. It may be clear that without financial and human resources, BM experimentation projects have only limited impact. As explained in Section 2, we focus on innovativeness as an outcome construct, i.e., as a capacity to produce innovations.

In general, the resources and characteristics of the firm have been shown to influence the capacity dimension of innovativeness (Hurley & Hult, 1998). This implies that, if companies have more resources available for innovation-related activities, the company will increase its capacity to innovate. From this, we draw our next hypothesis: more resources dedicated to BM experimentation positively contributes to innovativeness.

H1b. Resource allocation for BM experimentation has a direct effect on innovativeness (increased innovative output).

3.2. BM strategy implementation practices

The concept of ***BM strategy implementation practices*** refers to activities through which the strategy of the company is expressed in its BM, as extensively discussed in the literature (e.g., Al-Debei & Avison, 2010; Hedman & Kalling, 2003; Seddon et al., 2004). For instance, a retail company might recognize that competitors are using social media as a sales channel, which requires the company to change its channels in the BM. Another example is that a retail company makes the strategic choice to differentiate from competitors by delivering outstanding after-sales services, which requires changes in the activities of the BM. We follow the view that strategy needs to be implemented in the business logic as a first step in the BMI process. We posit that, after taking this first step, companies will experiment with alternative BMs that fit their strategy; for instance, trying out different configurations of social media channels. In this way, BM experimentation practices and innovation activities will be affected; for instance, if the strategic choice is to expand to international markets, BM experimentation practices will intensify by; for example, experimenting with new target groups or delivery channels. Therefore, we propose the hypothesis:

H2a. BM strategy implementation practices have a direct effect on BM experimentation practices.

Experimentation by firms have been shown to positively affect the success rate of innovations (Siguaw et al., 2006). Assuming that experimentation leads to learning, there is hence a conceptual link between the learning dimension of innovativeness and the act of experimentation within BMI (Chesbrough, 2010; Teece, 2010). Even failing BMI experimentation activities provide lessons on what works and can thus not only contribute to finding successful BMs (Chesbrough, 2010; McGrath, 2010), but also to the capacity to innovate of the firm. From this we draw our next hypothesis: engaging more in practices of implementing strategy to BM contributes to innovativeness.

H2b. BM strategy implementation practices have a direct effect on innovativeness (increased innovative output).

3.3. Performance antecedents

Innovativeness will impact the overall performance of the firm. Innovativeness orientation can have a positive effect on business performance as innovativeness translates into development of competitive advantage (Hult et al., 2004; Hurley & Hult, 1998). Firms interested in innovating will focus on activities that improve their capacity to do so (Hurley & Hult, 1998). This capacity drives firms to improve continuously and, thus, results in improved business performance. Therefore, we propose the next hypothesis:

H3. Innovativeness has a direct effect on the overall firm performance.

Business performance can be significantly affected by BM changes, as firms that are more focused on BMI outperform those that are not, in terms of profit (Giesen et al., 2007, 2010). An IBM CEO study reported that CEOs from top firms acknowledge the impact of BMI on the operation margin growth of their firms (Pohle & Chapman, 2006). BMI has become one of the three main innovation foci for CEOs to improve their firms' business performance. By innovating their BMs, firms can also gain competitive advantage, as BMs might be hard to replicate, thus resulting in firms' continued profitability (Chesbrough, 2006). The market share of a SME or start-up can also be positively affected by BM experimentation practices, as a novel BM can recombine existing internal resources or use those of external partners (Zott & Amit, 2007).

BM experimentation practices, as discussed before, relate to how BMI is actually realized, for example, what is done and in what order. Based on extensive case-study research (Heikkilä et al., 2018) and on the discussed literature (e.g., Chesbrough & Rosenbloom, 2002; Dunford et al., 2010; Khanagha et al., 2014), we found that, depending on what SMEs try to achieve, specific BM experimentation paths are followed. From this, we expect that the greater the effort firms put into experimenting with their BMs, the better their overall performance will be. Therefore, we propose the next hypothesis:

H4. BM experimentation practices have a direct effect on the overall firm performance.

It should be noted that, when we run the analysis to investigate path relationships, we also aim to examine whether innovativeness and BM experimentation practices mediated the path relationships between (a) resources for BM experimentation and (b) BM strategy implementation practices to overall firm performance. With the above defined concepts and how they affect the overall firm performance, the following research model is proposed and will be tested empirically (see Fig. 1).

4. Research method

In this section, we present the methods used in this study to examine and evaluate the proposed research model. Based on the above discussion, empirical research was conducted to examine how digitalization enables companies to change or innovate their current BMs. We used two approaches for data analysis: a conventional regression-based method (i.e., structural equation modelling [SEM]) as well as a configurational thinking method (i.e., fuzzy-set qualitative comparative analysis [fsQCA]) to investigate how combined conditions lead to an outcome.

SEM is especially applicable when dealing with relationships between constructs such as in the cases of resources for BM experimentation and subjective assessment of overall firm performance. SEM also allows for examining mediation effects, as proposed in our research model. In this study, partial least squares (PLS-SEM) method was used, which is a component-based estimation.

4.1. Survey administration, sample, and data collection

Our survey included SMEs that changed their BM because of digitalization. Specifically, we only selected SMEs that changed their BM in the past 24 months in response to the strategic decision to implement social media or big data technologies. To ensure the validity of responses, the questionnaire starts by asking whether the company changed its BM in the past 24 months. Next, a filter question asked whether the BM was changed due to the implementation of social media and/or big data. Only respondents that answered positively to the latter question were included in our sample.

The questionnaire was iterated and pretested, reading it aloud to managers and academics to improve the clarity of questions. The questionnaire was developed in English and then translated into 11 languages (i.e., Dutch, French, Finnish, German, Italian, Lithuanian, Polish, Portuguese, Slovenian, Spanish, and Swedish). The German version was used for Austria as well. In order to detect potential problems (e.g., ambiguous expressions) and cultural issues, back-translation of the questionnaire into English was performed to ensure that translation did not introduce any bias in the measures. Moreover, a final check on translations and consistency between the different language versions was done by a professional research agency. The questionnaire was pretested in every one of the 12 (the aforementioned 11 countries and Austria) countries.

Data were collected in 2017 by a professional research agency based in the Netherlands with extensive experience in data collection in multiple countries. Native speakers conducted the survey via computer-assisted telephone inquiry. The countries included in this research are spread over Europe and contain, for each European region (north, west, central, south, and east), a large country and small country with large number of SMEs. Quota for micro, small, and medium enterprises was established as 33% for each of the categories. There was no quota defined for industry sectors. Agriculture, public administration, and nonmarket activities in households were excluded. The sample was based on Dun and Bradstreet database. Dun and Bradstreet collects data on companies,

Table 1
Question items used in the study.

Construct & source	Items (7-point Likert scale, totally disagree – totally agree)
How did you deal with business model innovation during the last 12 months	
Resources for BM experimentation (Sosna et al., 2010)	Q3_1: Experimented with the (implementation of) their business model
	Q3_2: Had a specific team to manage business model changes
	Q3_3: Allocated budgets for business model experimentation
In your enterprise, business models are …	
BM strategy implementation practices (Ireland et al., 2009; Osterwalder et al., 2005)	Q4_1: Used to gain competitive advantages
	Q4_2: Designed in response to market circumstances
	Q4_3: Derived from enterprise's strategy
The Business Model innovation required	
BM experimentation practices	Q8_1: Changing the entire BM
Lindgardt et al., 2009; Teece, 2010	Q8_2: Changing only some components of the BM
	Q8_3: Changing product/service offering, before changing the BM
	Q8_4: Changing the BM, before changing the product/service offering
	Q8_5: Changing the BM and product/service offering at the same time
	Q8_6: Trying out new BMs in practice first, before making final changes
	Q8_7: In-depth analyses before starting to change the BM
In our enterprise, we are very satisfied with	
Overall firm performance	Q14_1: The sales growth of the enterprise
Venkatraman and Ramanujam (1986)	Q14_2: The profit growth of the enterprise
	Q14_3: Market Share
	Q14_4: Speed to market
	Q14_5: Penetration Rate
	Q14_6: Market Value
	Q14_7: Net Income
	Q14_8: Return on Investment (ROI)

their executives, industry classification, and contact information on a regular basis from chambers of commerce and other organizations. Companies were randomly selected from the database and respondents (owner or BMI manager) were interviewed. Data that would lead to identification of respondents were withheld from the researchers. As a further test, the respondents' suitability (Atuahene-Gima & Ko, 2001) to answer the questionnaire and their degree of knowledge (1 = *very limited knowledge*, 7 = *very substantial knowledge*) regarding the product/service on offer, business processes, and new product/service development was assessed. Mean responses were 6.7, 6.6, and 5.9, respectively, which indicates adequate knowledge levels.

4.2. Development of the measurement model

The PLS-SEM and fsQCA studies were both based on the same measurement model. An extensive review of extant literature on several disciplines—such as entrepreneurship, strategic management, and BMs—was conducted to obtain a list of measures from which to develop our own measurement model (see Table 1). For instance, regarding resources for BM experimentation, we follow the conceptualization by Sosna et al. (2010). They describe a case in which a company allocates a specific budget and assigns a team to conduct experiments with the BM. From this, we develop three items to measure resources for BM experimentation, relating to time and budget.

To measure BM strategy implementation practices, we consider the extent to which strategy is a driver for innovating BMs. We derive from Ireland, Covin, and Kuratko (2009) the idea that strategy is used to pursue competitive advantage. From Osterwalder et al. (2005), we borrow the idea that strategies and BMs need to be aligned, and that BMs should be defined according to the market situation.

BM experimentation practices are mainly discussed in conceptual and qualitative, process-oriented papers, and not in quantitative empirical papers. Hence, there were not validated or previously used survey scales that could easily be adapted. The survey items were therefore self-developed, inspired by definitions of concepts and qualitative findings in the literature. We follow Lindgardt et al. (2009) who argue that BMI constitutes of changing at least two elements or components of the BM. We develop several items (Q8_1–5) on changing multiple or even the entire BM, in concert or in sequence with changing the offering of the firm. From Teece (2010), we derive the idea that BMI is a learning process in which analysing, trying out and reflecting upon new BMs is an ongoing process. We develop two items (Q8_6 and Q8_7) in order to reflect this experimentation aspect of BMI. We ensured content validity by discussing the items in a team of BM researchers from different universities and by pretesting them with independent academic experts and business managers.

Overall firm performance was measured subjectively. Mc Dermott and Prajogo (2012) suggest that the use of subjective measures of performance is a valid proxy for the use of objective ones. We follow the conceptualization by Venkatraman and Ramanujam's (1986) that business performance constitutes of financial performance (e.g., sales growth, profitability, market value) and operational performance (e.g., market share, product quality). We used 8 items to cover both aspects.

Regarding innovativeness, we focus on the capacity to innovate rather than the orientation towards innovation, as explained in Section 2. Within the concept of capacity to innovate, three sub-dimensions are relevant: the mean number of innovation adoptions,

Table 2
Question items used in the study for innovativeness.

Sub-dimension of innovativeness	Definition in original source	Survey items (7-point Likert scale, totally disagree – totally agree. In our enterprise:
Mean number of innovations per year	Total number of innovation adoptions divided by the number of years when the adoptions occur (Subramanian & Nilakanta, 1996)	Q13_1: Our enterprise aims to create multiple innovations annually Q13_2: Creating more than one innovation at the same time is common practice in our enterprise
Mean time of innovation adoption	How early the firm adopt the innovations. Early adopters will have higher scores than late adopters (Subramanian & Nilakanta, 1996)	Q13_3: Our enterprise introduces innovations that are completely new to the market Q13_4: Our enterprise is one of the first to introduce innovations Q13_5: Our enterprise is able to identify new opportunities
Consistency of innovation adoption	How consistent the firms being early or late adopters (Subramanian & Nilakanta, 1996)	Q13_6: Our enterprise shows perseverance in turning ideas into reality Q13_7: Our corporate culture is focused on constant innovation

mean time of innovation adoption, and the consistency of adoption (Subramanian & Nilakanta, 1996). The consistency dimension refers to the idea that innovative firms can adopt multiple innovations rather than one single innovation, which is commonly discussed in literature (Damanpour, 1991; Hurley & Hult, 1998). From these three sub-dimensions, we developed 2 to 3 items for each dimension, as listed in Table 2.

To test the measurement model, the dataset was analysed using IBM SPSS v.24 for confirmatory factor analysis (CFA). Confirmatory factor analyses confirmed the original five factors structured (four latent variables and one outcome variable), proposed in our conceptual model (see Fig. 1).

4.3. Validity and reliability

Factor loading accounts for unidimensionality of measuring items. The value of factor loading for an established item should be 0.6 or higher. It is necessary to remove items from the measurement model if their factor loadings are low, one item at a time. Four items (from the BM experimentation practices construct: Q8_1, Q8_3, Q8_4, and Q8_6) were removed from further analyses due to low factor loadings. As can been seen in Table 3, all the remaining item loadings are above the recommended value. Moreover, Cronbach's

Table 3
Items descriptive statistics, convergent validity, internal consistency, and reliability.

Construct	*Items*	*Factor Loadings*	*Mean*	*Std. dev*	*t-statistic*	*α*[a]	*CR*[b]	*AVE*[c]
Resources for BM experimentation	Q3_1	0.87	3.75	2.04	46.70	0.796	0.880	0.710
	Q3_2	0.78	3.28	2.19	23.86			
	Q3_3	0.87	3.41	2.11	49.85			
Business model strategy implementation practices	Q4_1	0.85	4.98	1.98	45.96	0.772	0.867	0.686
	Q4_2	0.84	5.06	1.85	34.35			
	Q4_4	0.79	4.74	1.97	22.96			
BM experimentation practices	Q8_2	0.77	3.03	1.81	15.17	0.689	0.780	0.541
	Q8_5	0.73	3.99	1.87	14.05			
	Q8_7	0.70	4.90	1.97	11.81			
Innovativeness	Q13_1	0.80	4.77	1.71	26.94	0.877	0.905	0.577
	Q13_2	0.71	5.36	1.42	18.84			
	Q13_3	0.70	5.20	1.38	19.67			
	Q13_4	0.80	4.46	1.85	32.01			
	Q13_5	0.79	3.89	1.94	31.51			
	Q13_6	0.73	4.07	1.92	20.74			
	Q13_7	0.77	4.12	1.86	26.92			
Overall firm performance	Q14_1	0.81	4.58	1.63	30.48	0.911	0.928	0.616
	Q14_2	0.82	4.44	1.65	36.22			
	Q14_3	0.75	4.28	1.61	20.71			
	Q14_4	0.72	4.58	1.52	22.67			
	Q14_5	0.77	4.42	1.45	25.27			
	Q14_6	0.80	4.64	1.45	34.70			
	Q14_7	0.83	4.41	1.55	34.01			
	Q14_8	0.78	4.54	1.60	23.55			

Note. [a]: Cronbach's alpha; [b]: composite reliability; [c]: average variance extracted.

Table 4
Correlation among constructs and AVE square root.

	Resources for BM experimentation	BM strategy implementation practices	BM experimentation practices	Innovativeness	Overall firm performance
BM experimentation practices	0.736				
BM strategy implementation practices	0.318	0.828			
Innovativeness	0.274	0.540	0.759		
Overall firm performance	0.319	0.370	0.402	0.785	
Resources for BM experimentation	0.252	0.430	0.418	0.392	0.843

Note. Boldfaced values show AVE square roots.

alpha is a common test for internal reliability of latent constructs (Bryman & Bell, 2011) with a recommended value of 0.70 or higher (Hair, Ringle, & Sarstedt, 2011). Convergent validity is achieved by average variance extracted (AVE) values higher than 0.50 (Hair et al., 2011). All the constructs in Table 3 have sufficient convergent validity: AVE > 0.541. Finally, composite reliability (CR) examines the internal consistency and reliability of the constructs and it is recommended to be 0.70 or higher (Hair et al., 2011).

4.4. Discriminant validity

Discriminant validity guarantees the uniqueness of a measurement construct and indicates that the phenomenon of interest is not captured by other measures within the measurement model (Hair, Anderson, Babin, & Black, 2010; Henseler, Ringle, & Sarstedt, 2015). Scholars predominantly use the Fornell–Larcker criterion and cross-loadings for discriminant validity assessment in variance-based structural equation modelling. The classical criterion (i.e., Fornell–Larcker criterion) for discriminant validity assessment requires the square root of AVE to be greater than the correlation of the construct with all other constructs in the structural model. Table 4 shows that our measurement model fulfils the Fornell–Larcker criterion, indicating that the squared root of AVE exceeds the average correlation between latent constructs.

In this research, a second criterion—heterotrait–monotrait ratio (HTMT)—was used for assessing discriminant validity in PLS-SEM. HTMT is an alternative to the classical Fornell–Larcker criterion for assessing discriminant validity; it refers to the average heterotrait–heteromethod correlations measuring the relative to the average monotrait–heteromethod correlations. Monotrait–heteromethod is the correlation of indicators measuring the same construct and heterotrait–heteromethod is the correlation of indicators across constructs measuring different phenomena. HTMT value close to 1 indicates lack of discriminant validity; however, some authors (e.g., Henseler et al., 2015, p. 129) suggest a conservative value of 0.85 and a more liberal value of 0.90 for HTMT. According to this recommendation, if HTMT values are lower than 0.85, one can establish that discriminant validity is not an issue. Table 5 shows that HTMT values satisfy the more conservative criterion, as all were below 0.85.

5. PLS-SEM results

PLS-SEM was used to test the hypotheses. Overall firm performance is explained by 26% of the variance, BM experimentation practices is explained by 13% of the variance and innovativeness as an outcome is explained by 33% of the variance. Fig. 2 shows the relationships between constructs in the model. With regard to model fit, as we used PLS-SEM for the analysis, we report the standardized root mean square residual (SRMR) value, which is defined as the difference between the observed correlation and the model implied correlation matrix. SRMR allows assessing the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of (model) fit criterion. According to Hu and Bentler (1998), a value lower than 0.10, and in a more conservative consideration 0.08, is considered a good fit. Henseler et al. (2014) introduced the SRMR as a goodness-of-fit measure for PLS-SEM and recommend to use this measure to avoid model misspecification; our results show that the SRMR value is 0.067 for the estimated model, which indicates the model has a good fit.

Table 5
Heterotrait–monontrait ratio (HTMT).

	BM experimentation practices	BM strategy implementation practices	Innovativeness	Overall firm performance	Resources for BM experimentation
BM experimentation practices					
BM strategy implementation practices	0.468				
Innovativeness	0.367	0.653			
Overall firm performance	0.423	0.429	0.440		
Resources for BM experimentation	0.370	0.545	0.493	0.457	

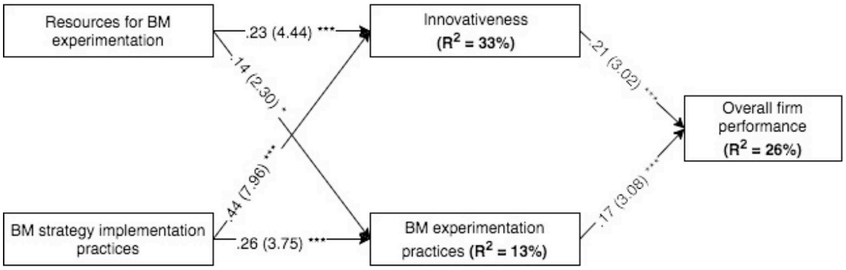

Fig. 2. Structural model results.
Note. ***$p < .001$. **$p < .005$. *$p < .01$.

Table 6
Hypotheses and results.

#	Hypotheses	Results
H1a	Resources for BM experimentation has a direct effect on BM experimentation practices.	Supported
H1b	Resources for BM experimentation has a direct effect on innovativeness.	Supported
H2a	BM strategy implementation practices have a direct effect on BM experimentation practices.	Supported
H2b	BM strategy implementation practices have a direct effect on innovativeness.	Supported
H3	Innovativeness has a direct effect on the overall firm performance.	Supported
H4	BM experimentation practices has a direct effect on the overall firm performance.	Supported

5.1. *Hypotheses testing*

Table 6 shows the research hypotheses and analysis results. The structural model results reveal that resources for BM experimentations has a positive relationship with BM experimentation practices as well as with the innovativeness, with significant path coefficients: ($\beta = 0.14$, $t = 2.31$, $p < .005$) and ($\beta = 0.23$, $t = 4.46$, $p < .001$), respectively. Thus, H1a and H1b are supported by the model. The results also show that BM strategy implementation practices has a positive relationship with the BM experimentation practices as well as with the innovativeness, with significant path coefficients: ($\beta = 0.26$, $t = 3.75$, $p < .001$) and ($\beta = 0.44$, $t = 7.96$, $p < .001$), respectively. Therefore, both H2a and H2b are supported by the model. Moreover, the PLS-SEM analysis reveals significant path relationships between innovativeness and overall firm performance ($\beta = 0.21$, $t = 3.02$, $p < .001$) and between BM experimentation practices and overall firm performance ($\beta = 0.17$, $t = 3.08$, $p < .001$). Thus, H3 and H4 are supported by the model.

5.2. *Mediation effect*

Furthermore, we performed mediation tests to see if the innovativeness and BM experimentation practices mediate the relationships between resources for BM experimentation and BM strategy implementation practices to the overall firm performance. The results show a positive direct relationship between resources for BM experimentation and overall firm performance ($\beta = 0.22$, $t = 3.68$, $p < .001$). The specific indirect effects test result show that innovativeness partially mediates the relationship between resources for BM experimentation ($\beta = 0.05$, $t = 2.33$, $p < .01$) and overall firm performance. Moreover, the results show that there is no significant direct relationship between BM strategy implementation practices and overall firm performance, however, the specific indirect effects result shows that innovativeness fully mediates the relationship between BM strategy implementation practices and the overall firm performance ($\beta = 0.10$, $t = 2.89$, $p < .001$). Additionally, a mediation test was performed to examine if BM experimentation practices mediates the relationship between resources for BM experimentation and BM strategy implementation practices on the overall firm performance. The results showed that BM experimentation practices partially mediates the relationship between BM strategy implementation practices and the overall firm performance ($\beta = 0.04$, $t = 2.044$, $p < .03$), as there is a significant direct relationship in this path. Finally, the mediation test results show that there is no mediation between resources for BM experimentation and overall firm performance through the BM experimentation practices, see Table 7 for more

Table 7
Mediation test results.

Specific Indirect Effects	β	*t-stat*	*p-value*	*Mediation*
BM strategy implementation practices - > innovativeness - > overall firm performance	.10	2.89	0.001	Full
Resources for BM experimentation - > innovativeness - > overall firm performance	0.05	2.33	0.01	Partial
BM strategy implementation practices - > BM experimentation practices - > overall firm performance	0.04	2.04	0.03	Partial
Resources for BM experimentation - > BM experimentation practices - > overall firm performance	0.02	1.85	0.06	No mediation

information).

6. Fuzzy-set qualitative comparative analysis

The PLS-SEM analysis showed that our hypotheses were supported and there were significant mediation effects. Thus, a rather complex theoretical model was produced. At the same time, the explained variance for overall firm performance (output construct) was moderate (26%). Therefore, through a qualitative configurational thinking method (fsQCA), we argue that we may be able to explain overall performance better by adopting a wider array of causal assumptions.

Fuzzy-set qualitative comparative analysis (fsQCA) was developed by Ragin (1987) and since its conception has been used in various disciplines and has recently gathered considerable attention in business and strategy management studies (see e.g., Brännback, Nikou, & Bouwman, 2017; Liu, Mezei, Kostakos, & Li, 2017; Munoz & Cohen, 2017). FsQCA uses set theory and can be employed to assess causal complexity and the possibility of multiple solutions with different combinations of conditions. This method overcomes some of the limitations of traditional quantitative methods such as regression analysis. For instance, conventional regression-based analysis shows the results as linear relationships, whether positively or negatively related, whereas fsQCA presents the outcome as multiple configurations comprising combinations of causal conditions (Fiss, Cambré, & Marx, 2013). Causal conditions, in terms of fsQCA, are assessed as necessity and sufficiency. In this paper, a condition (e.g., resources for BM experimentation) is necessary if the outcome of interest (i.e., overall firm performance) cannot be produced without it, and a condition is sufficient if it can produce the outcome by itself without the help of other conditions (Ragin, 2008). FsQCA encompasses three important implications that make it a complementing approach for explaining complex phenomena. First, fsQCA assumes that there can be many pathways to the same outcome (referred to as equifinality[4]). Second, it assumes each pathway can contain different combinations of conditions, thus seeking for the effect of combinations (also known as configurations) of necessary and sufficient conditions, rather than seeking for the net effect of each individual condition with the same importance. Third, it requires to carefully convert (the process is known as calibration) data into set membership by means of theoretical and substantive knowledge external to the empirical data (Ragin, 2008).

Moreover, multiple regression analysis is criticized for assuming the existence of a linear relationship between constructs in models, whereas fsQCA allows assessing asymmetric relationships between antecedent conditions and the outcome of interest. Recent literature on business and strategy management shows an increasing interest for alternatives to statistical methods, partly motivated by the increasing popularity of qualitative comparative analysis (QCA) as developed in the 1970s (Beynon, Jones, & Pickernell, 2016; Roig-Tierno, Alc´azar, & Ribeiro-Navarrete, 2015). In addition, fsQCA enables to account for how conditions jointly produce a certain outcome (Ragin, 2000; Ragin & Fiss, 2008). By using fsQCA, we are able to analyse the combined effects and causal connections among conditions (e.g., resources for BM experimentation and BM strategy implementation practices) in relation to the outcome (i.e., overall firm performance; Ragin, 2000, 2014). Therefore, consistent with our research model and PLS-SEM results, we advance the following proposition for the fsQCA study:

Proposition 1. *SMEs' overall business performance can be explained as a combination of resources for BM experimentation, BM strategy implementation practices, innovativeness, and BM experimentation practices.*

To analyse the complex causality in the data and proceed with the fsQCA, we followed the next four steps.

6.1. Calibration

In the first step, in order to prepare the data for running the fsQCA analysis, we calibrate (transforming raw data into fuzzy-set membership values between 0 and 1) conditions (i.e., resources for BM experimentation, BM strategy implementation practices, BM experimentation practices, and innovativeness) and the outcome condition (overall firm performance) into fuzzy sets. Values of the membership scores or fuzzy sets range from 0 to 1 on a continuous scale. A value of 0 indicates an absence of set membership (full nonmembership or completely out of the set), and a value of 1 indicates full set membership (or completely in the set). Ragin (2008) and Woodside (2013) state that degree of membership for each condition can be defined by setting three qualitative anchors: full membership (fuzzy score = 0.95), full nonmembership (fuzzy score = 0.05), and crossover point (fuzzy score = 0.50). It has been argued that consistent calibration rules can be used for the explanatory variables (conditions), where the crossover point can be set to the median, and full nonmembership and full membership can be set to the 10th and 90th percentile, respectively (Linton & Kask, 2017; Tóth, Thiesbrummel, Henneberg, & Naudé, 2015).

As input for the calibration, we constructed a factor score for each latent construct by computing the average of the items belonging to that construct according to our measurement model (validated in Section 4). In this way, the PLS-SEM and fsQCA models used identical input data. As these aggregate scores range between 1 and 7, to transform values into fuzzy sets, we followed the procedure recommended by Ordanini, Parasuraman, and Rubera (2014). Full membership was set at values over 6, the crossover-point at 4, and full nonmembership at 2.

[4] Equifinality means the coexistence of multiple paths to a desired outcome (i.e., different causal variables may cause the same outcome).

Table 8
Assessment of necessity of causal conditions.

Condition	Consistency	Coverage
Resources for BM experimentation	0.608 (0.740)	0.881 (0.686)
BM strategy implementation practices	0.919 (0.425)	0.738 (0.814)
BM experimentation practices	0.742 (0.746)	0.899 (0.792)
Innovativeness	0.823 (0.701)	0.890 (0.831)

Note. Values for condition negation are shown within parentheses.

6.2. Analysis of necessary conditions

In the second step, we assessed whether there were any conditions that could be identified as necessary for the outcome to occur. This assessment is called necessity analysis (Ragin, 2006). The analysis of necessary conditions determines if any of the four conditions used in this research can be considered as necessary for causing the outcome. In other words, it means we need to examine whether a single condition is always present or absent in all cases where the outcome is present (or absent; Fiss, 2007; Ragin, 2006). When the necessity analysis is computed, the consistency and coverage values for the presence as well as the absence (negation) of each condition are obtained. A high value indicates that the presence/absence of a condition might be seen as necessary for the occurrence of the outcome. A condition is considered as necessary if the consistency value exceeds the recommended threshold of 0.9 (Schneider & Wagemann, 2010). Consistency measures the degree to which the cases align to the particular rule: the more cases that fail to meet this rule for necessary condition, the lower will be the consistency score (Ragin, 2006). Table 8 shows that there is one condition (BM strategy implementation practices) with consistency value over 0.90, which can therefore be seen as a necessary condition for the outcome to occur. This high value may imply that, in a large number of cases specified by the coverage value, overall firm performance can only be present if the condition *BM strategy implementation practices* is satisfied. However, it does not mean that high value for this condition automatically imply high level of overall firm performance. For the rest of the conditions, we can see that none of them exceed the threshold (both their presence as well as their absence), and thus are not necessary for the outcome to occur.

6.3. Analysis of sufficient conditions

The third step entails the construction of a truth table (Fiss, 2011; Ragin, 2000, 2006, 2008). We constructed a truth table with the explanatory measures with columns and rows representing possible combinations of conditions, and an additional column for the outcome. The number of rows should be 2^k to list all possible combinations, since we have four conditions, the truth table consists of 16 possible causal combinations. Furthermore, the truth table should be reduced to contain only meaningful configurations, which is decided based on their frequency of empirical instances. The frequency cut-off value (i.e., minimum number of cases in the rows) must be decided and, in this case, the substantive domain knowledge of the researcher plays an important role. If no frequency cut-off value is defined, only rows with zero cases should be removed from the truth table. However, Ragin (2008) has recommended, in addition to zero cases, to remove configurations that consist of only one or two cases. The minimum number of cases in this study was set to three, meaning that configurations with two or less observations were treated as “remainders” when building our truth table. In addition, a minimum acceptable level of consistency should be defined for the remaining rows to classify configurations as either sufficient or not sufficient for the outcome to occur, or the degree to which a specified configuration shows the desired outcome. It is recommended to set the minimum level of consistency at 0.75 (Ragin, 2006, 2008; Woodside, 2013), which we did. Some researchers (e.g., Wu, Yeh, Huan, & Woodside, 2014) argue that consistency value in fsQCA is analogous to correlation in statistical analysis. In the final step of truth-table construction, based on Boolean algebra, we used the Quine–McCluskey algorithm to reduce the truth table rows to simplified solutions.

6.4. Evaluation of solutions

By applying the Quine–McCluskey minimization procedure, three different solution sets can be identified: parsimonious, intermediate, and complex. Complex solution offers the most important solutions (more difficult to interpret), parsimonious solution in general offers oversimplified solutions, and intermediate solution uses only a subset of the simplified assumptions that are used in the parsimonious solution. The interpretation of the intermediate solutions requires extensive knowledge on the cases and the relationships between individual conditions and the outcome (Ragin, 2008). Fiss (2011) pointed out that the conditions can be divided into core and peripheral with respect to a specific configuration; core conditions appear in both parsimonious and intermediate solutions and peripheral conditions only appear in intermediate solutions.

Finally, when the fsQCA solutions are obtained, two important measures can be used to determine the fit of each configuration: consistency and coverage. First, consistency measures the extent to which a configuration corresponds to the outcome (Ragin, 2008). Configurations exceeding the cut-off value (≥ 0.75) can be considered as sufficient for achieving the outcome (Ragin, 2008). Second, the coverage measure assesses the proportion of cases that follow a particular path and captures the empirical importance of an identified configuration (Fiss, 2007). The raw coverage quantifies the proportion of memberships in the outcome explained by each

Table 9
Intermediate solutions for overall performance*.

Solution	S1	S2	S3	S4
Resources for BM experimentation	●			
BM strategy implementation practices		●		
BM experimentation practices			○	●
Innovativeness			●	○
Raw coverage	0.608	0.919	0.674	0.595
Unique coverage	0.007	0.101	0.010	0.003
Consistency	0.882	0.838	0.911	0.930
Overall solution coverage	0.95			
Overall solution consistency	0.83			

Note. *Black circles indicate the presence of a condition and blank circles indicate its absence. Blank spaces indicate "do not care."

term of the configuration, while the unique coverage measures the proportion explained solely by one solution excluding memberships that are covered by other solutions (Ragin, 2006). As the unique coverage of each configuration exceeds the value of zero, each solution contributes to the explanation of the outcome (otherwise it should be eliminated).

6.5. FsQCA results

Next, we present the results of the fsQCA, which were obtained based on the causal configuration of four conditions (see Table 9). As mentioned before, the aim was to identify the causal configurations of the four conditions—resources for BM experimentation, BM strategy implementation practices, BM experimentation practices, and innovativeness—leading to the outcome of interest (i.e., overall firm performance). Before presenting the results, it is necessary to mention that we used the following notations, as proposed by Ragin and Fiss (2008): Black circles (●) indicate the presence of a condition and blank circles (○) indicate its absence. Blank spaces indicate "do not care," in other words, the causal condition may be either absent or present.

The fsQCA results show four configurations (see Table 9). In terms of coverage values, the results show an overall solution coverage score of 0.95, which means that the four configurations of causal conditions explain 95% of the overall firm performance. The four solutions present acceptable overall solution consistency (> 0.83). Consistency indicates the degree to which the solution is sufficient for producing the outcome and it measures the degree to which a subset relation has been approximated. Ragin (2006) recommends that a consistency threshold should not be lower than 0.75, which is the one that we adopted. Thus, solutions that did not adhere to this requirement were not included in the analyses. Moreover, coverage value indicates the degree to which cases correspond to the (combination of) conditions.

According to fsQCA results, Solution 1 indicates that the presence of resources for BM experimentation is enough to lead to the outcome of interest. In other words, this solution suggests that resource (time and budget) allocation for BM experimentation is a sufficient condition for achieving high firm performance. Specifically, it indicates that greater availability of resources allows for firms' performance whether a firm is successfully implementing its strategy in their BM or not, the firm experiments with their BM or not, and whether the firm is becoming more innovative or not. This conclusion is illustrated by the blank space for these three conditions that signals a "do not care" situation. Solution 2 shows that the presence of BM strategy implementation practices leads to the occurrence of the outcome—increased firm performance; however, from the consistency standpoint, this solution has the lowest value (0.838) of the four configurations obtained. It is striking that innovativeness, which serves as a mediating construct in the SEM model, plays a role in two configurations (Solutions 3 and 4). Solution 3 indicates that the presence of innovativeness and the negation (absence) of BM experimentation practices lead to the outcome of interest. Finally, solution 4 indicates that the negation (absence) of innovativeness and the presence of BM experimentation practices lead to the outcome of interest. From the consistency perspective, solution 4 has the highest consistency value (0.930).

7. Discussion

There has been an increasing number of papers discussing the relation between BMI and firm performance (Gronum et al., 2015; Teece, 2010; Zott & Amit, 2007, 2008). We contribute to this stream of research by showing that the resources and activities dedicated to BMI affect firm performance, partly mediated by the capacity to innovate. Although research on BM and performance is increasing, research with a focus on SMEs is lagging behind.

Moreover, the results show that firms can improve their performance through (a) allocating more resources for BM experimentation and (b) enhancing their capacity to innovate either by increasing the number of innovation or spending more time for innovation. Our results are not only consistent with previous findings (e.g., Chesbrough, 2010; Kraus, Brem, Schüssler, Schüssler, & Niemand, 2017; Trimi & Berbegal-Mirabent, 2012) showing that innovation is a key success factor for the firm performance, and that BMI is a vehicle for the firm transformation, but also confirm earlier Zott's et al. (2011) finding that argue BMI is the key to firm performance. In addition, the importance of innovativeness confirmed by both PLS-SEM and fsQCA results indicate that BMs represent a component of innovation commercialization that is managed separately, but in accordance with the value innovation process (George & Bock, 2011).

Moreover, our results reveal an important practical issue which is the availability of resources, such as know-how and technologies vis-à-vis business activities and what these imply for a BM. Although business people might know the business logic in detail, understanding where and how new digital technologies can be used and how they would impact the BM is in area in which IT people might have more expertise. BMs help to visualize the impact of strategic decisions with regard to digitalization implementation into the business logic and the needed resources for BM experimentation. Communication of BM changes should be encouraged as well. Our literature search on BMI and new digital technologies such as social media and big data for non-telecommunications or non-IT companies show limited contributions (Mack, Marie-Pierre, & Redican, 2017). Moreover, it was also found that literature on BMs in the telecommunications and IT domain is mainly focused on large companies and high-tech start-ups. Thus, the impact of technologies on traditional SMEs' BMs is a field largely open for new avenues of research. Among handful studies in this domain, Mikalef and Pateli (2017, p. 10–11) have used both PLS-SEM and fsQCA approaches to conceptualise the IT-enabled dynamic capabilities as the capacity to effectively leverage IT for the digitization and firm competitive performance. While, the results of causal mechanisms obtained through PLS-SEM show that IT-enabled dynamic capabilities, mediated by organizational agility, largely improve firm competitive performance. The fsQCA results emphasise the importance of IT-enabled dynamic capabilities for achieving firm competitive performance.

8. Conclusions, limitations, and future work

This quantitative study provides an overall picture of the relations between strategy implementation into the business logic, resources for BM experimentation, and BM experimentation practices. In this paper, overall firm performance was the primary outcome of interest and was measured using four constructs: (a) resources for BM experimentation, (b) BM strategy implementation practices, (c) BM experimentation practices, and (d) innovativeness. This was analysed in the context of 321 European SEMs firms' experimenting with their BMI during the last 12 months. Our paper is among the first to show the performance implications of conducting BM experimentation and strategy implementation. We show that allocating resources for BM experimentation pays off, as it leads to increased levels of BM experimentation and, indirectly, to higher frim performance. We applied two different methods and both, i.e., PLS-SEM and fsQCA results provide important insights into BMI and performance for SMEs, specifically for SMEs engaged in digital transformation and when strategic decisions in relation to social media and big data are involved.

While, both the PLS-SEM and fsQCA studies consistently show that BM experimentation and strategy implementation contribute to performance, the results are different in important ways. On the one hand, the PLS-SEM study suggests that spending time and resources on BM experimentation and strategy implementation both contribute to overall firm performance, mediated by higher levels of innovativeness and BM experimentation practices. One the other hand, the fsQCA, from the complexity theory standpoint, while reinforce and refine findings of the PLS-SEM results, recognizes that no single condition is the cause of an outcome of interest—several conditions act in combination to cause an outcome of interest to occur. In this study, the fsQCA results show possible combinations of conditions driving overall firm performance. This can be further demonstrated by the presence of equifinality, that is, identifying various configurations of causal conditions to produce the outcome. Specifically, the fsQCA results suggest that there are different ways to boost performance and that higher performing firms either choose to spend their efforts on BM experimentation or on strategy implementation. Moreover, as the PLS-SEM study shows innovativeness plays an important role, mediating the relationships between resources for BM experimentation as well as BM strategy implementation and the overall firm performance. The fsQCA also shows that innovativeness is an important condition in two configurations (Solutions 3 and 4).

This paper theoretically contributes to a better understanding of the effect of digitalization in the context of BMI. It offers practical insights into how BM experimentation impacts performance and innovativeness, specifically for BMI driven by digitalization. Another contribution of this paper is geared towards policymakers and practitioners. For instance, the results of this paper imply that policies aimed at the encouraging SEMs to utilize the business opportunities brought about by digitalization must be oriented toward stimulating SMEs to use information technology, big data and social media as a means for practicing more on BM experimentations as well as implementing new strategies. This is the more relevant because more fundamental developments related to digital transformation, like Internet-of-Things, Smart industry, machine learning, artificial intelligence, smart services and comparable "technologies" will require SMEs to reconsider their BM.

This research has some limitations, which are related to both the quantitative nature of the study and the fact that SMEs are diverse in terms of their operation fields. In addition, this study was conducted in Europe, in many different languages, and with cultural and economic differences despite the context of a common market. There are also some limitations with regard to our research design. We specifically focused on firms that are knowingly or unknowingly engaged in BMI. Research comparing companies involved in BMI and firms not engaged in BMI might provide deeper insights into the drivers of digital transformation. In addition, some of the measurement items used in this paper were based on subjective judgments; connecting these subjective judgments with actual performance data would be interesting, however, this is not possible due to European rules in relation to research ethics and informed consent. A final limitation, as in any cross-sectional study, is that the direction of causality cannot be inferred from the data alone. Alternative theorizations are possible, including feedback loops—for instance, that BM experimentation makes companies more innovative and high-performing, which in turn helps freeing up resources for BM experimentation.

We are aware that there is also a reverse causality, as more innovative firms have faster innovation cycles, which fosters their processes of BMI (Vazquez, Santos & Alvarez, 2001). We are aware that innovativeness may lead to new (technological) innovations which in turn require changes in BMs (Giesen et al., 2010; Calia, Guerrini & Moura, 2007). In future research, our focus will be on collecting another wave of data in order to establish causalities more clearly, as well as on expanding our insights into how BMI actually takes place, using case studies. We are also aware that this research has only dealt with a small part of a vast area of research.

In the future, the aim will be to focus in more detail on how firms experiment with their BMs, how BM components are affected, and how implementation approaches with regard to human and organizational factors affect BMI performance. Insights into BM experimentation practices are also relevant for future tool development, since more tools are being developed to support BM experimentation and implementation (Bouwman et al., 2008; De Reuver, Bouwman, & Haaker, 2013; Haaker, Bouwman, Janssen, & de Reuver, 2017).

In current BM literature with an empirical focus, little attention has been paid to specific technological contexts such as digital transformation (see Cavalcante, 2014, for an exception). This paper is a first to position BMI within a context of digitalization. Complementing these results with case studies as those presented by Bouwman, de Reuver, and Nikou (2017) would give more detailed insights. Thus, more in-depth understanding of BM experimentation based on case studies is necessary. Specifically, BM experimentation practices need closer analysis to understand the steps and paths taken by firms. Also, the order in which BM components are changed is an important issue to study further. Understanding BMI paths and roadmaps to implementation is important for SMEs. BMI paths need to be analysed to see how digital transformation works in relation to certain technologies, either with a focus on business growth or on profitability. In Heikkillä (2018), we can see that these choices also lead to a distinct focus on components, that is, an orientation to value proposition and customer interaction or to making resources and activities available at lower costs. Thus, future studies could further delve into this issue. For instance, it can be assumed that technology characteristics play a crucial role in the incremental or radical nature of the BMI, for instance, its modularity or recombinability. Moreover, it would be important to know in which BM activities and business processes these technologies play a role. This would also imply that the conceptual model (see Fig. 1) needs to be tested for specific technologies individually. Finally, it is important to stress that big data might have a huge impact on BMI and firm performance; thus, exploring big-data-driven BMs would be a very relevant research domain for future studies. Additionally, in the context of understanding business digitalization, research on the impact of new technologies within traditional as well as emerging industry sectors such as digital marketing or Industry 4.0, is highly relevant.

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Appendix A. Supplementary data

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References

Achtenhagen, L., Melin, L., & Naldi, L. (2013). "Dynamics of business models –strategizing, critical capabilities and activities for sustained value creation". *Long Range Planning, 46*(6), 427–442.

Al-Debei, M. M., Al-Lozi, E., & Al-Hurjan, O. (2015). "Critical Design an evaluation factors of mobile business models. "Road Block" eradications for mobile network operators". *Journal of Enterprise Information Management, 28*(5), 698–717.

Al-Debei, M. M., & Avison, D. (2010). Developing a unified framework of the business model concept. *European Journal of Information Systems, 19*(3), 359–376.

Aspara, J., Hietanen, J., & Tikkanen, H. (2010). Business model innovation vs. replication: Financial performance implications of strategic emphases". *Journal of Strategic Marketing, 18*(1), 39–56.

Atuahene-Gima, K., & Ko, A. (2001). An empirical investigation of the effect of market orientation and entrepreneurship orientation alignment on product innovation. *Organization Science, 12*(1), 54–74.

Aziz, S. A., & Mahmood, R. (2011). The relationship between business model and performance of manufacturing small and medium enterprises in Malaysia. *African Journal of Business Management, 5*(22), 8918–8932.

Baden-Fuller, C., & Morgan, M. S. (2010). Business models as models. *Long Range Planning, 43*(5), 156–171.

Ballon, P. (2007). Business modelling revisited: The configuration of control and value. *Info, 9*(5), 6–19.

Barjak, F., Es-Sadki, N., & Arundel, A. (2014). The effectiveness of policies for formal knowledge transfer from European universities and public research institutes to firms. *Research Evaluation, 24*(1), 4–18.

Berends, H., Smits, A., Reymen, I., & Podoynitsyna, K. (2016). Learning while (re-)configuring: Business Model Innovation in established firms. *Strategic Organization, 14*(3), 181–219.

Beynon, M. J., Jones, P., & Pickernell, D. (2016). Country-based comparison analysis using fsQCA investigating entrepreneurial attitudes and activity. *Journal of Business Research, 69*(4), 1271–1276.

Bharadwaj, A., El Sawy, O., Pavlou, P., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471–482.

Björkdahl, J., & Magnus, H. (2013). "Editorial: Business model innovation – the challenges ahead". *International Journal of Product Development, 18*(3–4), 213–225.

Bock, A. J., Opsahl, T., George, G., & Gann, D. M. (2012). The effects of culture and structure on strategic flexibility during business model innovation. *Journal of Management studies, 49*(2), 279–305.

Bonakdar, A. (2015). *Business model innovation*Doctoral dissertation University of St. Gallen. Retrieved from http://verdi.unisg.ch/www/edis.nsf/SysLkpByIdentifier/4334/$FILE/Dis4334.pdf.

Bouwman, H., de Reuver, M., & Nikou, S. (2017). The impact of digitalization on business models: How IT artefacts, social media, and big data force firms to innovate their business model. Kyoto, Japan *Proceeding of 14th international telecommunications society (ITS) asia-pacific regional conference: "Mapping ICT into transformation for the next information society* (pp. 24–27). June 2017.

Bouwman, H., Haaker, T., & De Vos, H. (2008). *Mobile service innovation and business models.* Heidelberg: Springer.

Brännback, M., Nikou, S., & Bouwman, H. (2017). Value systems and intentions to interact in social media: The digital natives. *Telematics and Informatics, 34*(4), 365–381. https://doi.org/10.1016/j.tele.2016.08.018.

Bryman, A., & Bell, E. (2011). *Business research methods* (3rd ed.). New York: Oxford University Press Inc.

Bucherer, E., Eisert, U., & Gassmann, O. (2012). Towards systematic business model innovation: Lessons from product innovation management. *Creativity and Innovation Management, 21*(2), 183–198.

Casadesus-Masanell, R., & Ricart, J. E. (2010). From strategy to business models and onto tactics. *Long Range Planning, 43*(2), 195–215.

Casadesus-Masanell, R., & Zhu, F. (2013). Business model innovation and competitive imitation: The case of sponsor-based business models. *Strategic Management Journal, 34*(4), 464–482.
Cavalcante, S. A. (2013). "Understanding the impact of technology on firms' business models". *European Journal of Innovation Management, 16*(3), 285–300.
Cavalcante, S. A. (2014). "Preparing for business model change: The "pre-stage" finding". *Journal of Management & Governance, 18*(2), 449–469.
Chesbrough, H. (2006). *Open business models: How to thrive in the new innovation landscape.* Boston: Harvard Business Press.
Chesbrough, H. (2010). Business model innovation: Opportunities and barriers. *Long Range Planning, 43*(2), 354–363.
Chesbrough, H., & Rosenbloom, R. S. (2002). "The role of business model in capturing value from innovation: Evidence from Xerox Corporation's technology spin-off companies". *Industrial and Corporate Change, 11*(3), 529–555.
Clausen, T., & Rasmussen, E. (2013). Parallel business models and innovativeness of research-based spin-off ventures. *The Journal of Technology Transfer, 38*(6) 386-849.
Clauss, T. (2017). Measuring business model innovation: Conceptualization, scale development, and proof of performance. *R & D Management, 47*(3), 385–403.
Cortimiglia, M. N., Ghezzi, A., & Frank, A. G. (2016). "Business model innovation and strategy making nexus: Evidence from a cross-industry mixed-methods study". *R & D Management, 46*(3), 414–432.
Cucculelli, M., & Bettinelli, C. (2015). Business models, intangibles and frim performances: Evidence on corporate entrepreneurship from Italian manufacturing SMEs. *Small Business Economics, 45*(2), 329–350.
Dahan, N. M., Doh, J. P., Oetzel, J., & Yaziji, M. (2010). Corporate-NGO collaboration: Co-creating new business models for developing markets. *Long Range Planning, 43*(2–3), 326–342.
De Reuver, M., Bouwman, H., & Haaker, T. (2013). Business model road mapping: A practical approach to come from an existing to a desired business model. *International Journal of Innovation Management, 17*(1), 1–18.
Dijkman, R. M., Sprenkels, B., Peeters, T., & Janssen, A. (2015). Business models for the internet of things. *International Journal of Information Management, 35*(6), 672–678.
Dunford, R., Palmer, I., & Benveniste, J. (2010). Business model replication for early and rapid internationalization. *Long Range Planning, 43*(5–6), 655–674.
EASME (2015). *Horizon 2020's SME instrument.* Retrieved from http://ec.europa.eu/easme/en/horizons-2020-sme-instrument, Accessed date: 20 March 2019.
El Sawy, O. A., & Pereira, F. (2013). Visor: A unified framework for business modelling in the evolving digital space. *Business modelling in the dynamic digital space* (pp. 21–35). Springer Berlin Heidelberg.
European Commission (2017). *Female entrepreneurs.* Retrieved from: https://ec.europa.eu/growth/smes/promoting-entrepreneurship/we-work-for/women_en, Accessed date: 20 March 2019.
Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review, 32*(No. 4), 1180–1198.
Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal, 54*(2), 393–420.
Fiss, P. C., Cambré, B., & Marx, A. (2013). *Configurational theory and methods in organizational research.* Emerald Group Publishing.
Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: How far have we come, and where should we go? *Journal of Management, 43*(1), 200–227.
Frankenberger, K., Weiblen, T., Csik, M., & Gassmann, O. (2013). The 4I-framework of business model innovation: A structured view on process phases and challenges. *International Journal of Product Development, 18*(3–4), 249–273.
Garcia, R., & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: a literature review. Journal of Product Innovation Management: An International Publication of the Product Development & *Management Association, 19*(2), 110–132.
George, G., & Bock, A. J. (2011). The business model in practice and its implications for entrepreneurship research. *Entrepreneurship: Theory and Practice, 35*(1), 83–111.
Giesen, E., Berman, S. J., Bell, R., & Blitz, A. (2007). Three ways to successfully innovate your business model. *Strategy & Leadership, 35*(6), 27–33.
Giesen, E., Riddleberger, E., Christner, R., & Bell, R. (2010). When and how to innovate your business model. *Strategy & Leadership, 38*(4), 17–26.
Gronum, S., Steen, J., & Verreynne, M. L. (2015). Business model design and innovation: Unlocking the performance benefits of innovation. *Australian Journal of Management, 41*(3), 585–605.
Gruber, H. (2018). Proposals for a digital industrial policy for Europe. *Telecommunications Policy, 43*(2), 116–127. https://doi.org/10.1016/j.telpol.2018.06.003.
Haaker, T., Bouwman, H., Janssen, W., & de Reuver, M. (2017). Business model stress testing: A practical approach to test the robustness of a business model. *Futures, 89*, 14–25.
Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). *Multivariate data analysis* (7th ed.). Englewood Cliffs: Prentice Hall.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–151.
Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2016). "Capturing value from big data – a taxonomy of data-driven business models used by start-up firms". *International Journal of Operations & Production Management, 36*(10), 1382–1406.
Hayashi, A. M. (2009). Do you have a" plan B? *MIT Sloan Management Review, 51*(1), 10–11.
Hedman, J., & Kalling, T. (2003). The business model concept: Theoretical underpinnings and empirical illustrations. *European Journal of Information Systems, 12*(1), 49–59.
Heikkilä, M., Bouwman, H., & Heikkilä, J. (2018). From strategic goals to business model innovation paths: An exploratory study. *Journal of Small Business and Enterprise Development, 25*(1), 107–128.
Heikkilä, M., & Heikkilä, J. (2013). Collaborative business model innovation process for networked services. *International conference on electronic commerce* (pp. 133–147). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-39808-7_12.
Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., et al. (2014). Common beliefs and reality about partial least squares: Comments on rönkkö & evermann (2013). *Organizational Research Methods, 17*(2), 182–209.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
Huang, H. C., Lai, M. C., Kao, M. C., & Chen, Y. C. (2012). Target costing, business model innovation, and firm performance: An empirical analysis of Chinese firms. *Canadian Journal of Administrative Sciences, 29*(1), 322–335.
Hu, L.-t., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*(4), 424–453.
Hult, G. T. M., Hurley, R. F., & Knight, G. A. (2004). Innovativeness: Its antecedents and impact on business performance. *Industrial Marketing Management, 33*(5), 429–438.
Hurley, R. F., & Hult, G. T. M. (1998). Innovation, market orientation, and organizational learning: An integration and empirical examination. *Journal of Marketing, 62*(3), 42–54.
Ireland, R. D., Covin, J. G., & Kuratko, D. F. (2009). Conceptualizing corporate entrepreneurship strategy. *Entrepreneurship: Theory and Practice, 33*(1), 19–46.
Khanagha, S., Volberda, H., & Oshri, I. (2014). Business model renewal and ambidexterity: Structural alteration and strategy formation process during transition to a C loud business model. *R & D Management, 44*(3), 322–340.
Kiel, D., Arnold, C., Collisi, M., & Voigt, K. I. (2016). The impact of the industrial internet of things on established business models. *Proceedings of the international association for management of technology (IAMOT)* (pp. 673–695). Orlando, FL, May 15-19.
Kim, S., & Min, S. (2015). Business Model Innovation Performance: When does adding a new business model benefit an incumbent? *Strategic Entrepreneurship Journal, 9*(4), 34–57.
Kraus, S., Brem, A., Schüssler, M., Schüssler, F., & Niemand, T. (2017). Innovative born Globals: Investigating the influence of their business models on international performance. *International Journal of Innovation Management, 21*(1), 1–54.
Lambert, S. C., & Davidson, R. A. (2013). Applications of the business model in studies of enterprise success, innovation and classification; an analysis of empirical research from 1996 to 2010. *European Management Journal, 31*(6), 668–681.

Lee, Y., & O'Connor, G. C. (2003). The impact of communication strategy on launching new products: The moderating role of product innovativeness. *Journal of Product Innovation Management, 20*(1), 4–21.

Lindgardt, Z., Reeves, M., Stalk, G., & Deimler, M. S. (2009). *Business model innovation. When the game gets tough, change the game.* Boston, MA: The Boston Consulting Group.

Linton, G., & Kask, J. (2017). Configurations of entrepreneurial orientation and competitive strategy for high performance. *Journal of Business Research, 70*, 168–176. https://doi.org/10.1016/j.jbusres.2016.08.022.

Liu, Y., Mezei, M., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: A methodological alternative for modelling combinatorial complexities. *Information Systems Journal, 27*(1), 59–89.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems, 24*(3), 149–157.

Lucas, H. C., Agarwal, R., Clemons, E. K., El Sawy, O. A., & Weber, B. (2013). Impactful research on transformational information technology: An opportunity to inform new audiences. *MIS Quarterly, 37*(2), 371–382.

Mack, E. A., Marie-Pierre, L., & Redican, K. (2017). “Entrepreneurs' use of internet and social media applications”. *Telecommunications Policy, 41*(2), 120–139. https://doi.org/10.1016/j.telpol.2016.12.001.

Markides, C., & Sosa, L. (2013). Pioneering and first mover advantages: The importance of business models. *Long Range Planning, 46*(4–5), 325–334.

Martins, L., Rindova, V., & Greenbaum, B. (2015). Unlocking the hidden value of concepts: A cognitive approach to business model innovation. *Strategic Entrepreneurship Journal, 9*(1), 99–117.

Mc Dermott, C. M., & Prajogo, D. I. (2012). Service innovation and performance in SMEs. *International Journal of Operations & Production Management, 32*(2), 216–237.

McGrath, R. G. (2010). Business models: A discovery driven approach. *Long Range Planning, 43*(1), 247–261.

Methlie, L. B., & Pedersen, P. E. (2007). Business model choices for value creation of mobile services. *Info, 9*(5), 70–85.

Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research, 70*, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004.

Munoz, P., & Cohen, B. (2017). Mapping out the sharing economy: A configurational approach to sharing business modelling. *Technological Forecasting and Social Change, 125*(December 2017), 21–37. https://doi.org/10.1016/j.techfore.2017.03.035.

Ordanini, A., Parasuraman, A., & Rubera, G. (2014). When the recipe is more important than the ingredients: A qualitative comparative analysis (QCA) of service innovation configurations. *Journal of Service Research, 17*(2), 134–149.

Osterwalder, A., Pigneur, Y., & Tucci, C. L. (2005). Clarifying business models: Origins, present, and future of the concept. *Communications of the Association for Information Systems, 16*(1), 1–25.

Pohle, G., & Chapman, M. (2006). “IBM's global CEO report 2006: Business model innovation matters. *Strategy & Leadership, 34*(5), 34–40.

Rachinger, M., Rauter, R., Müller, C., Vorraber, W., & Schirgi, E. (2018). Digitalization and its influence on business model innovation. *Journal of Manufacturing Technology Management*. https://doi.org/10.1108/JMTM-01-2018-0020.

Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies.* Berkeley. CA: University of California Press.

Ragin, C. C. (2000). *Fuzzy-set social science.* University of Chicago Press.

Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis, 14*(3), 291–310.

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond.* Chicago, IL: University of Chicago Press.

Ragin, C. C. (2014). *The comparative method: Moving beyond qualitative and quantitative strategies.* University of California Press.

Ragin, C. C., & Fiss, P. C. (2008). Net effects analysis versus configurational analysis: An empirical demonstration. In C. C. Ragin (Ed.). *Redesigning social inquiry: Fuzzy sets and beyond: 190–212*. Chicago: University of Chicago Press.

Roig-Tierno, N., Alc´azar, J., & Ribeiro-Navarrete, S. (2015). Use of infrastructures to support innovative entrepreneurship and business growth. *Journal of Business Research, 68*(11), 2290–2294.

Schneider, C. Q., & Wagemann, C. (2010). Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets. *Comparative Sociology, 9*(3), 397–418.

Seddon, P., Lewis, G., Freeman, P., & Shanks, G. (2004). The case for viewing business models as abstractions of strategy. *Communications of the Association for Information Systems, 13*(1), 427–442.

Siguaw, J. A., Simpson, P. M., & Enz, C. A. (2006). Conceptualizing innovation orientation: A framework for study and integration of innovation research. *Journal of Product Innovation Management, 23*(6), 556–574.

Sosna, M., Trevinyo-Rodriguez, R. N., & Velamuri, S. R. (2010). Business model innovation through trial-and-error learning. *The Naturhouse Case”, Long Range Planning, 43*(1), 383–407.

Souto, J. E. (2015). Business model innovation and business concept innovation as the context of incremental innovation and radical innovation. *Tourism Management, 51*, 142–155.

Spieth, P., & Schneider, S. (2016). „Business models innovativeness: Designing a formative measure for business model innovation”. *Journal of Business Economics, 86*(6), 671–696.

Subramanian, A. (1996). Innovativeness: Redefining the concept. *Journal of Engineering and Technology Management, 13*(2), 223–243.

Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning, 43*(1), 172–194.

Tikkanen, H., Lamberg, J. A., Parvinen, P., & Kallunki, J. P. (2005). Maagerial cognition, action and the business model of the firm. *Management Decision, 34*(6), 789–809.

Tóth, Z., Thiesbrummel, C., Henneberg, S. C., & Naudé, P. (2015). Understanding configurations of relational attractiveness of the customer firm using fuzzy set QCA. *Journal of Business Research, 68*(3), 723–734.

Trimi, S., & Berbegal-Mirabent, J. (2012). Business model innovation in entrepreneurship. *The International Entrepreneurship and Management Journal, 8*(4), 449–465.

Turber, S., vom Brocke, J., Gassmann, O., & Fleisch, E. (2014). Designing business models in the era of internet of things. In M. C. Trenblay (Ed.). *DESRIST, 2014, LNCS 8463* (pp. 17–31). .

Unruh, G., & Kiron, D. (2017). *Digital transformation on purpose.* MIT Sloan Management Review. November 6, available at https://sloanreview.mit.edu/article/digital-transformation-on-purpose/ accessed March 20 2019) .

Veit, D., Clemons, E., Benlian, A., Buxmann, P., Hess, T., Kundisch, D., Leimeister, J. M., et al. (2014). Business models: An information systems research agenda. *Business & Information Systems Engineering, 6*(1), 45–53.

Velu, C., & Jacob, A. (2016). Business model innovation and owner-managers: The moderating role of competition. *R & D Management, 46*(3), 451–463.

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly, 37*(1), 21–54.

Venkatraman, N., & Ramanujam, V. (1986). Measurement of business performance in strategic research. *Academy of Management Review, 11*(4), 801–814.

Waldner, F., Poetz, M. K., Grimpe, C., & Eurich, M. (2015). Antecedents and consequences of business model innovation: The role of industry structure. In C. Baden-Fuller, & M. Vincent (Vol. Eds.), *Business models and modelling (advances in strategic management: Vol 33*, (pp. 347–386). Emerald Group Publishing Limited.

Walravens, N. (2015). Qualitative indicators for smart city business models: The case of mobile services and applications. *Telecommunications Policy, 39*(3–4), 218–240.

Wirtz, B. W., Göttel, V., & Daiser, P. (2016). Business model innovation: Development, concept and future research directions. *Journal of Business Models, 4*(1), 1–28.

Wirtz, B. W., Schilke, O., & Ullrich, S. (2010). Strategic development of business models: Implications of the web 2.0 for creating value on the internet. *Long Range Planning, 43*(No 2/3), 272–290.

Woodside, A. G. (2013). Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research, 66*(4), 463–472.
Wu, P. L., Yeh, S. S., & Woodside, A. G. (2014). Applying complexity theory to deepen service dominant logic: Configural analysis of customer experience-and-outcome assessments of professional services for personal transformations. *Journal of Business Research, 67*(8), 1647–1670.
Zott, C., & Amit, R. (2007). Business model design and the performance of entrepreneurial firms. *Organization Science, 18*(2), 181–199.
Zott, C., & Amit, R. (2008). The fit between product market strategy and business model: Implications for firm performance. *Strategic Management Journal, 29*(1), 1–26.
Zott, C., & Amit, R. (2010). Business model design: An activity system perspective. *Long Range Planning, 43*(2), 216–226.
Zott, C., Amit, R., & Massa, L. (2011). The business model: Recent developments and future research. *Journal of Management, 37*(4), 1019–1042.