Business model innovation in European SMEs: thriving configurations and performance implications

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Executive Summary

For many years, Business Model Innovation (BMI) has been recognized by academics as key to improve competitiveness and innovativeness. While more than ninety percent of the large corporates conduct some degree of BMI (Lindgardt & Ayers, 2014), BMI has barely reached Small and Medium enterprises (SMEs). Increasing the use of BMI in SMEs is believed to boost the economic situation, which has become the objective of multiple innovation support programs (European Commission, 2015).

To substantiate the need for these programs and to guide their actions, the link between BMI and business performance requires clarification. Based on a dataset collected in 2016 by project ENVISION, this study investigates this relation by examining over five hundred European SMEs. From the approached SMEs, about one in seven recognizes BMI and uses it. To accommodate with this low number, this study focuses on SMEs that made some changes in their BM.

Following the view that BMI is an organizational change process, SMEs are investigated regarding their engagement in two important phases of BMI: BM experimentation and BM implementation. Together, we refer to these practices as the level of BMI engagement. The findings off this study provide evidence that both phases contribute to business performance independently.

By means of clustering techniques, this study investigates whether some parts of the populations are more engaged in BMI than others. Focusing on four firm characteristics (firm age, firm size, gender of CEO and family/non-family enterprise), we identify and compare configurations of firms based on their average BMI engagement and performance. We find that smaller SMEs are less engaged in BMI compared to larger SMEs and that SMEs with male CEOs are in general more engaged in BMI than firms with female CEOs. Moreover, we find that older SMEs are more engaged than younger SMEs and that non-family SMEs are more engaged than family SMEs, although these differences do not apply to all clusters in the data.

An implication of this study is that BMI can positively affect firm performance in different ways. Since only a small part of the European SMEs is engaged in BMI, their lies valuable room to enhance this number and improve the current economic situation. Therefore, this study substantiates the need for policy programs aimed at enhancing BMI adoption in SMEs. Our results provide directions on how programs can be tailored to parts of the SME population that are expected to show the strongest response to raising BMI adoption. European policy makers should use these directions to scope their efforts and stimulate adoption in several parts of the European SME population.

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List of abbreviations

BMEX	business model experimentation
BMI	business model innovation
BMIM	business model implementation
ENVISION	empowering SME business model innovation
CFA	confirmatory factor analysis
EA	enterprise architecture
EFA	exploratory factor analysis
fsQCA	fuzzy set qualitative comparative analysis
LCA	latent class analysis
OM	operating model
PERF	perceived business performance
PI	prime implicant
SEM	structural equation model
SME	small and medium enterprise

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Chapter 1 Introduction

The products we buy and services we use are changing with increasing rate. Within the time span of only a few generations, the industry has faced multiple revolutions. From the first industrial revolution enabling mechanical mass production, to the invention of electricity and recently the invention of internet that boosted global connectivity and shared knowledge. Today, the industry is at the start of yet another revolution that can be characterised by industrial automation and implementation of complex machine interactions.

The impact of these industry transitions is massive and requires firms to quickly adapt to an ever-changing environment. These changes result in firms innovating their value propositions, offering new products and services to customers. More drastically, they require firms to change the way they do business: strategic changes that reflect in the firm's business model (BM). During a global CEO study several years ago, one of the CEOs stated, "products and services can be copied; the business model is the differentiator"(Pohle & Chapman, 2006).

The importance of changes in BMs is increasingly recognized by researchers, managers and policy makers. But how do firms change their BM and how can these changes be measured and compared across firms? And is investing in business model innovation enough to experience its beneficial outcomes, or is this in reality not as easy as some want us to believe?

1.1 Problem statement

It is a widely held view that innovations serve as crucial instrument for companies to becoming resilient in the tough economic environment (e.g. Drucker, 1985; Pisano, 2015; Rao, Ahmad, Horsman, & Kaptein-Russell, 2001). Innovations exist in many different forms and are commonly classified by two types. They can be technological, such as product and process innovation, or non-technological, such as organizational innovation or Business Model Innovation (BMI). BMI, referring to changes in the Business Model, is a concept that is increasingly discussed in literature on (macro)management and strategic management, and that is recognized as object of study in an emerging scientific field (Foss & Saebi, 2017b).

BMI is perhaps the most radical form of innovation since it involves many complexities of organizational change. For practitioners, BMI can be a costly, time consuming process that is not easy to implement. For scientists, it remains difficult to measure BMI in a consistent way and develop congruence on what is and what is not BMI. This makes BMI a challenging but rewarding construct to study, because its implications can be of great societal and scientific relevance.

Policy makers are recognizing the importance of BMI and take actions accordingly. To boost adoption of BMI in SMEs, the European Commission included resources for initiatives that support BMI in the Horizon 2020 Research and Innovation Program (EC, 2011). BMI is not easily promoted since it involves many different aspects, including but not limited to raising awareness, training activities and the development of well-designed supporting tools. One Europe-wide initiative supported by H2020 is ENVISION, a project designed to enhance the innovative capacity of SMEs. The objective of ENVISION is to contribute to practice and simultaneously study project participants, the results of which can advance the BMI literature (ENVISION, 2016). The present study will use the data collected by the ENVISION project to study implications of BMI in SMEs. While many contributions to the BMI literature motivate their need by the presumed beneficial consequences of BMI, few articles explain in detail how BMI strengthens firm performance (Dunford, Palmer, & Benveniste Jodie, 2010). As pointed out by Foss and Saebi (2017), an explanation for this low number can be the complexity of linking BMI to performance and the lack of conceptual congruence. This gap needs to be filled to advance the literature and to validate the motivations for BMI research and support.

The objective of this study is to investigate the causal effect of BMI engagement, which we define as the level of activity in BM experimentation and BM implementation, on business performance in the context of SMEs. The study will follow the idea that BMI can be studied as a process consisting of different phases, which include BM experimentation and BM implementation. The effect of these phases on performance will be investigated and compared between firms with different firm characteristics. Addressing these relations is important for both theory and practice. For the scientific field, it is important that suitable operationalizations of BMI are found and that performance implications are clarified in empirical studies. For practice, these relations have managerial relevance and policy makers may be especially interested on how these practices can differ across populations. There is a need to explore the relation between BMI and business performance because if this relation can be better understood, there is a potential to intervene and improve the performance of businesses.

1.2 Knowledge gap

The term BMI is rising in the literature. Today, more than hundred academic articles noting the term BMI are published annually (Figure 1). Despite this increase, the BMI literature is still young and key analytical constructs and assumptions regarding the phenomenon are not yet established. This has resulted in a lack of coordination and research efforts that branched off in various directions.

From a practical view, there exist many ways by which a firm can be involved in BMI. While some managers may follow an active strategy for BMI, others may make similar changes intuitively. BM changes in companies can take place because of arbitrary circumstances without a structural focus of the company on BMI. This has contributed to the complexity that is involved in studying BMI. Hence, BMI has been referred to as "a slippery construct to study", because it is difficult to define the necessary changes in BM justifying the term BMI (Casadesus-Masanell & Zhu, 2013).

Until now, most of the academic work has focused on BMI in large corporates. Likely, this is due to that large corporates possess most resources that can be allocated for BMI practices and go through complex innovation cycles that can offer interesting examples for case studies. In a recent observational study on large corporates, it was found that 94% of the CEOs reported that their companies had attempted some degree of BMI (Lindgardt & Ayers, 2014). The work on BMI in small and medium sized enterprises (SMEs) is increasing but scarce. BMI in SMEs needs further investigation, especially since BMI is underrecognized among SME managers and thus most societal relevance hides in this context.

One of the gaps in the literature that needs attention is the link between BMI and business performance (Foss & Saebi, 2017b). Companies continuously paying attention to BMI are likely to be more successful than their competitors who neglect the changing environment. From a scientific perspective, to date there is little evidence to support this thesis, predominantly because (1) BMI is not easy to measure (Clauss, 2017), (2) interventional studies are very complicated and have not been performed to date, and (3) observational data may be in support of the concept but cannot yield a direct evidence.

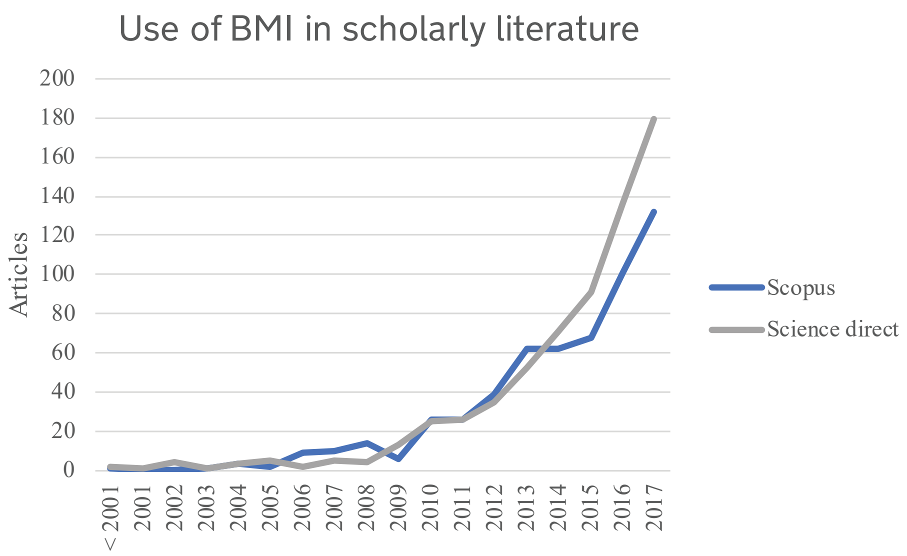


Figure 1 Use of BMI in scholarly literature. Source: Scopus (March 2018), searched in the field of "social sciences", "humanities" and "business, management and accounting" 1990-2017. "business model innovation" (BMI), 562 hits. Science direct, during the period of 1990-2017, "business model innovation" (BMI), 655 hits.

To address this gap in the literature, empirical studies are needed that relate BMI to performance. Ideally, BMI is measured in longitudinal studies that identify performance changes over time. This approach is rather difficult in practice, since data collecting is expensive. As recently pointed out, a starting point is to collect cross-sectional data on BM changes and regress those data against business performance (Foss & Saebi, 2017b).

From the small pool of studies that relate BMI to its outcomes, the clear majority test models on the whole dataset rather than on a subpopulation. For most datasets, there is no opportunity to investigate subsamples as the number of candidates quickly drops below significant levels. However, when the data set is sufficiently large, it is interesting to investigate clusters and to compare subgroups in the data. Relatedly, Kraus et al. (2017) point out the need to study causal configurations of BMI and firm performance. Taken this, there are opportunities to contribute to the literature in different ways.

First, our goal is to investigate the relation between BMI and performance. We pursue an empirical approach to investigate performance implications. Therefore, the study attempts to provide a direct contribution to this knowledge gap in the literature.

Second, our study focuses on this relation in SMEs. Until now, most academic work has focused on large corporates and studying SMEs, therefore, provides opportunities to study BMI in a novel context. Additionally, SMEs are an interesting context for BMI studies, since they provide severe economic relevance. Since the adoption of BMI is lower in SMEs than in large corporates, most economic potential hides in this area. Thus, our study focuses on a group of firms that is interesting for theory, since the context is novel, and for policy makers, since the findings may come with considerable economic relevance.

Third, our objective is to explore potential differences between different groups of SMEs. Focusing on multiple firm characteristics, we explore and compare configurations of SMEs. This could reveal insights on how firm characteristics play a role in BMI engagement. The results of this analysis may be of particular interest for policy makers, who aim to monitor and stimulate BMI engagement at the population level. Hence, our study investigates BMI engagement to an extent that goes beyond most studies in the field, and that may provide fruitful insights for policy makers.

1.3 Research scope

SMEs are commonly classified by three groups: micro, small and medium sized firms. Firms with less than 10 employees and a balance sheet total below €2 Million are referred to as micro sized firms. Firms with more than 9 and less than 50 employees with a balance sheet total under €10 Million are classified as small and bigger firms with up to 249 employees and a balance sheet total of €43 Million or lower are classified as medium (Table 1).

Company Category	Employees	Turnover	Balance sheet total
Micro	< 10	< €2 Million	< €2 Million
Small	< 50	< €10 Million	< €10 Million
Medium	< 250	< €50 Million	< €43 Million

Table 1 Classification of SMEs.

The current project focusses on SME in EU Member states. Small and medium businesses comprise the majority of companies in the EU and are responsible for the employment of more than 60% of people and generate over half of the revenues in the non-financial business sector (Figure 2)(Muller et al., 2016). This broad sector consists of all sectors of the economies of the EU-28 Member States, except 'financial services', 'government services', 'education', 'health', 'arts', 'culture' and 'agriculture, forestry, and fishing'.

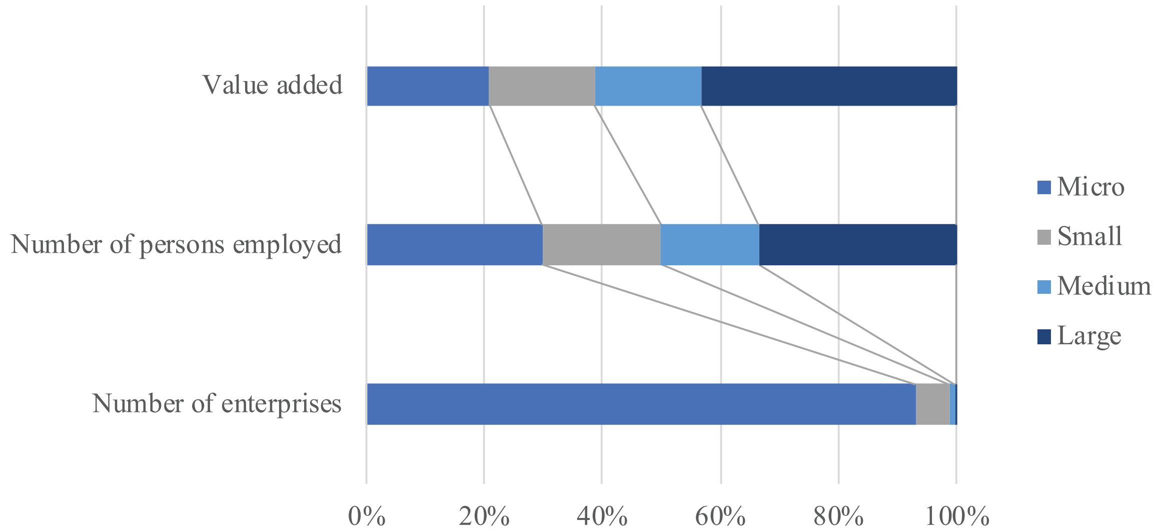


Figure 2 SMEs in 2016 in the EU-28 non-financial business sector.

Following the financial crisis in 2008, SME showed a decrease of 4.2% in 5 years which was more pronounced than the change of the total economy (-3.0%). This decrease was followed by a strong growth of 5.2% from 2013-2016 (Muller et al., 2016). These data show that SMEs are very sensitive to general changes in the economy (Figure 3).

To accommodate with changing environments and to stay competitive, BMI can be of crucial importance. While this notion is well recognized by practitioners in larger companies, managers of SMEs have hold back in this regard. This makes SMEs an interesting object for studying BMI, because findings can come with considerable societal relevance.

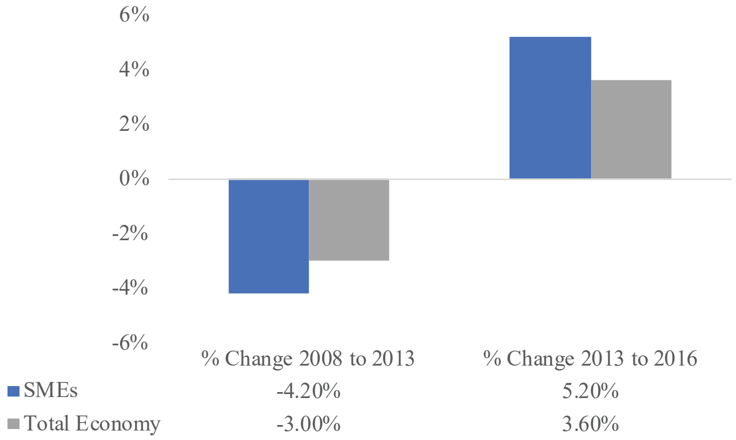


Figure 3 Change in economy-wide employment.

1.4 Research objective

In response to the mentioned conceptual gaps in the current literature, this study focuses on the following main research question:

Research question: To what extent does BMI engagement enhance business performance in European SMEs?

To obtain a comprehensive answer to this question, five sub questions are formulated that build up to achieve a desired answer.

Sub question 1. In what ways has BMI been linked to business outcomes in the literature?

As a start, the research domain needs to be investigated and existing contributions need to be overviewed to clarify how this relation has been studied by others. This will help to compare different ways of measurements of essential constructs and give insights in to obtained results. The answer to this question helps to place the current study in perspective.

Sub question 2. To what extent are European SMEs engaged in BMI?

Before studying the relation of these concepts, it is studied to what extent SMEs are engaged in BMI. One could consider two aspects when answering this question. First, one could question to what extent European SMEs are engaged in BMI at the population level. In other words, when looking at the situation of the European SME economy, what frequency of SMEs is engaged in BMI?

Next, one could ask to what extent the engaged firms are engaged. This question involves a quantification of the level of engagement. To put differently, when focusing on the SMEs that are engaged in BMI, what level of engagement is observed? Together, these questions provide an answer to sub question 2.

Sub question 3. Are there differences in BMI engagement depending on structural firm characteristics?

This question will be relevant for policy makers, since an answer provides insights that can be applied to the current economic situation. The literature reports a wide range of firm characteristics that can be used as moderators for effects on firm performance (e.g. Abbasi & Malik, 2015; Hsu, Chen, & Cheng, 2013). Firm characteristics can be analysed using three criteria: structure, market and capital. Structural firm characteristics include firm size, ownership and age. Market related characteristics involve environment and industry type, while capital related characteristics involve capital intensity and liquidity (Muhindi Kisengo & Kombo, 2014). Structural firm characteristics have been the focus of many scholars, since this group was found to be more related to organizational performance than the others (Kipesha, 2013). In this study, the focus will be on four structural firm characteristics, namely: firm age, size, gender of CEO, and family versus non-family enterprise.

Sub question 4. What is the effect of BMI engagement on business performance?

Finally, the study aims to provide understanding on the relation of BMI engagement on business performance. As recently overviewed, BMI can be conceptualized in different ways (Foss & Saebi, 2017c). A notable difference can be made between scholars who consider BMI as an outcome and scholars who study BMI as an organizational process. This study follows the idea that BMI is an iterative organizational process consisting of multiple phases that can have separate links to performance. Studying BMI as an "act", which can be implemented by managers, can provide great managerial relevance. When specific practices are found to affect performance, there is a potential to intervene and improve the performance of businesses that do not actively engage in these practices. Although the literature theoretically acknowledges the importance of different phases such as BM experimentation and BM implementation (Berends, et al., 2014; Cavalcante, 2014; Frankenberger et al., 2013), the interaction between these phases has not received much attention. In this study, we suggest a mediating role for BM implementation in the relation of BM experimentation to performance.

Sub question 5. Are the relations between BMI engagement and firm performance in subpopulations similar or do they differ dependent on firm characteristics?

To investigate whether potential effects caused by subgroups, comparison of this model will be done across groups with different firm characteristics. This question serves two purposes. First, it can help to compare to importance of BMI engagement across different subgroups of SMEs. The recognized importance of BMI may differ considerably in certain subgroups, and these differences can be revealed during these comparisons. On the other hand, this question can serve as control. Comparing the significance of relations across subgroups can help to evaluate the external validity of findings.

1.5 Research approach

To achieve satisfying answers for these questions, the study pursues a multi-method approach involving different techniques for multivariate analyses (Figure 4). The first question relies primarily on theoretical reasoning based on recent contributions in the BMI literature.

For the subsequent questions, a measurement model will be proposed and validated. Argumentation will be given for chosen operationalizations, and validation of the measurement model will be done by a confirmatory factor analysis (CFA).

The second question will be answered by means of descriptive statistics. The analysis will be done on cross-sectional data collected by the ENVISION project. The dataset was collected in the year 2016, and thus provides a near actual reflection of the current economic situation. The dataset involves information on BMI-related concepts from 586 SMEs originating from different sectors and European countries. An overview of BMI engagement will be obtained by overviewing frequencies of firms engaged in BMI and comparing average responses to particular items.

Sub question three will be studied by two techniques. To evaluate the effect of firm characteristics on BMI engagement, a latent class (cluster) analysis (LCA) will be done using the Latent GOLD software package.

By adding firm characteristics individually as covariates, interdependencies between firm characteristics and latent variables will be revealed and compared. Next, a fuzzy set qualitative comparative analysis (fsQCA) will be performed to identify and compare conditions that add up to explain firm performance. This method will serve to provide corroborative evidence for observed LCA findings and will be used to identify and compare configurations. Where LCA can be a powerful tool to study changes in cluster profiles by adding single characteristics as covariates, fsQCA can be a valuable extension to the analysis as it combines information from multiple characteristics simultaneously. Originating from fuzzy-set logic and Boolean algebra, fsQCA is a configurational comparative method that can be used to explore and compare configurations. Firm characteristics will be used as conditions on top of the BMI related latent variables to identify conditions that permeate most in the outcome. There exist different software packages for fsQCA analysis such as the fsQCA3.0 software package developed by Ragin and Sean (2016), and R by means of Package QCA developed by Dusa et al. (2018). Here, the analyses are based on the R software packages because of its flexibility to different approaches allowing us to implement robustness test that are not easily done in traditional analyses.

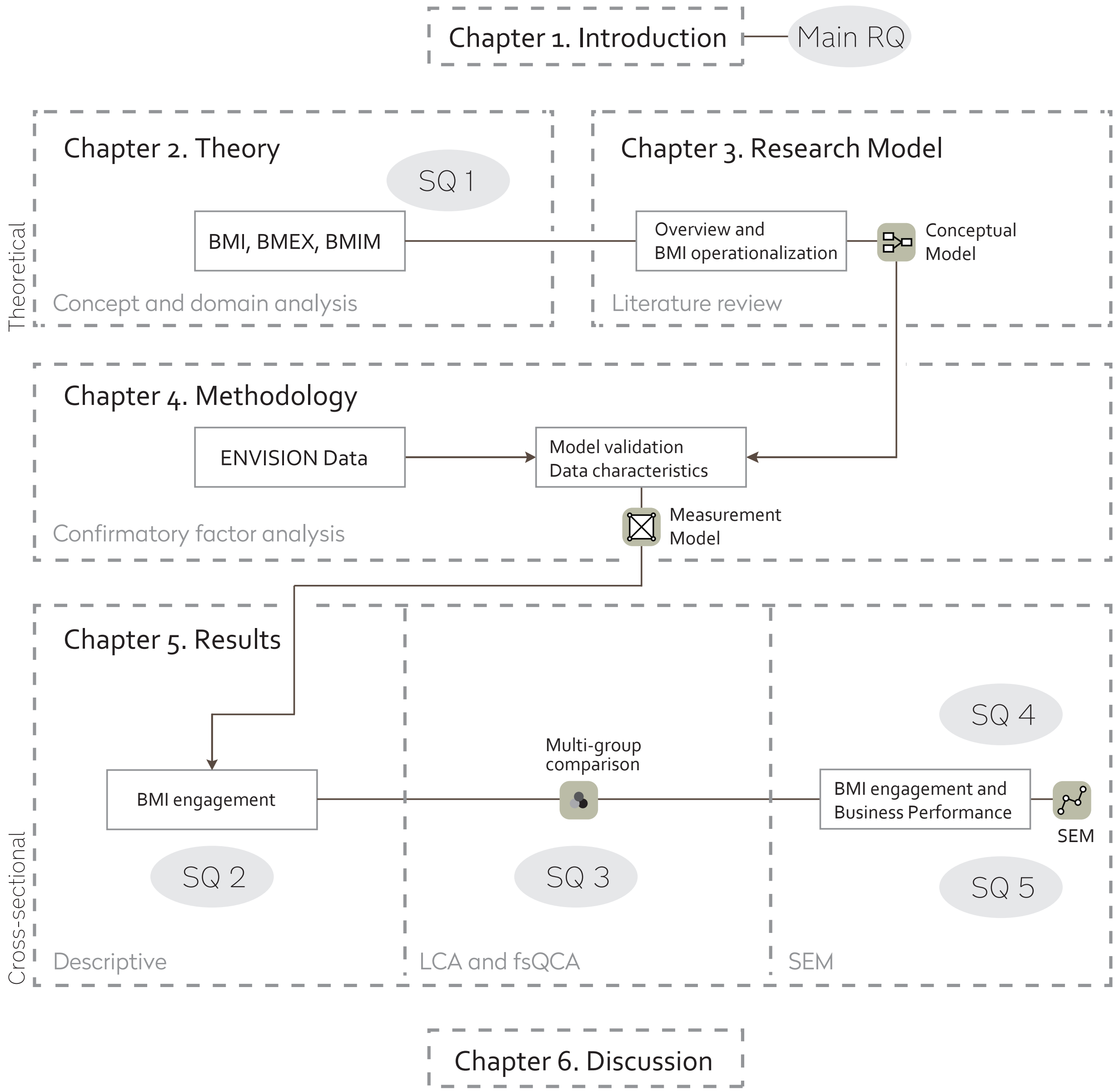


Figure 4 Research flow diagram.

The last two sub questions will be investigated by a regression-based approach. Since this study relies on cross-sectional data, the extent to which the direction of causality can be confirmed is limited. Despite this shortcoming, several confirmatory techniques are available that provide measures for evaluation of causal relations in cross-sectional studies. In this study, the confirmatory technique structural equation modelling (SEM) will be used to investigate causal effects between the concepts under investigation. SEM is a commonly used method for empirical studies and enables evaluation of a model consisting of multiple relations. Several software packages are available that can be used for SEM analyses, including but not limited to LISREL, MPlus, Stata, R and AMOS. In this study, AMOS is used because of its ease-of-use and compatibility with SPSS.

1.6 Structure

This Chapter introduced the research question under investigation and presented the approach that will be followed to obtain a comprehensive answer to this question. The next Chapter provides a brief discussion on the research domain and introduces relevant literature. Chapter three overviews some recent contributions on the relations under investigation and proposes an operationalization for BMI in the context of SMEs. This Chapter ends with the proposition of conceptual models and related hypothesis. The methodology and analysis approaches will be described in Chapter four. In the same Chapter, sample characteristics will be provided, and a comparison of method-related assumptions will be given. Chapter five will present the results for the SEM, LCA and fsQCA analyses in that order. Additionally, this Chapter contains a section on the comparison of results across different techniques. Chapter six summarizes main findings and discusses theoretical and practical implications which will be separated in theoretical, methodological and policy-related sections. This will be followed by a discussion on limitations and finally, an overview of avenues for future research.

Chapter 2 Literature

This Chapter will overview contributions in the literature and elaborate on the key concepts. First, a brief overview will be given on the BM and BMI literature. Next, argumentation will be given for the conceptualization of BMI engagement in this study. Then, studies investigating consequences of BMI will be overviewed and attention will be given to the features of SMEs and how this can affect BMI practices.

2.1 Business model

In the past decades, the concept of Business Model has been a focus of attention of many academics and practitioners originating from different fields and industries, which has resulted in a growing number of definitions and conceptualizations. Today, the notion of a Business Model has been mentioned in over thousand peer reviewed academic articles. Several scholars have attempted to overview the literature, providing insights in different Business model typologies and available classifications (e.g. Wirtz et al., 2016; Zott, Amit, & Massa, 2011).

As criticized by Zott et al. (2011), literature streams have been developing in silos, according to the themes of interest of respective scientists, which has led to a lack of conceptual consensus in the literature. Consequently, this led to the development of distinct conceptualizations that are addressed under the umbrella of the Business Model (Table 2). Even at a general level, a wide variety of terms have been used to refer to the Business Model, including but not limited to an architecture, framework, model or template (Zott et al., 2011). Despite these discrepancies, a few necessary elements seem to return in most definitions. Recent reviews indicate that many contributions converge to agree on five essential elements: (1) the firm's value proposition, (2) the market segment it addresses, (3) the structure of the value chain, (4) the mechanisms of value capture, and (5) the ways by which these elements are linked in an architecture (Saebi, Lien, & Foss, 2017; Wirtz et al., 2016).

Different scholars have criticised that the existing literature has mostly followed a static perspective on Business Models (Lindner et al., 2010; Putten et al., 2012). An emerging notion is that the focus should be on the dynamics of Business Models (Saebi et al., 2017). For example, Demil and Lecocq (2010) have discussed the importance of Business Model evolution, "a fine tuning process involving voluntary and emergent changes in and between permanently linked core components". Teece (2010) has discussed the concept of Business Model learning, which was referred to as modifications in incumbent Business Models in face of competition from a new Business Model. Other scholars have discussed the concept of Business Model renewal (Doz & Kosonen, 2010), replication (Dunford et al., 2010), transformation (Aspara et al., 2013) and adaptation (Saebi et al., 2017). These examples indicate a recent shift in academic literature and highlight the increasing focus on changes in the Business Model.

Relatedly, scholars have argued that Business Models should be investigated with regard to their implementation, and that there is a need to develop approaches to analyze the viability and feasibility of Business Models (Bouwman, De Vos, & Haaker, 2008; Teece, 2010). Hence, Solaimani (2014) argues the success of a BM cannot be determined by outputs that brainstorm sessions in design phases may yield, and that careful analysis of operational details is of essential importance.

Taken this, an increasing number of scholars have acknowledged the need to shift the focus to dynamics of BMs and the analysis of viability of intended changes. Given our focus on BMI, we follow a general definition of Wirtz et al. (2016), which includes this consideration and involves the previously mentioned dimensions of Business Models:

"A business model is a simplified and aggregated representation of the relevant activities of a company. It describes how marketable information, products and/or services are generated by means of a company's value-added component. In addition to the architecture of value creation, strategic as well as customer and market components are taken into consideration, in order to achieve the superordinate goal of generating, or rather, securing the competitive advantage. To fulfill this latter purpose, a current business model should always be critically regarded from a dynamic perspective, thus within the consciousness that there may be the need for business model evolution or business model innovation, due to internal or external changes over time."

Year	Author	Definition
1998	Timmers	The business model is "an architecture of the product, service and information flows, including a description of the various business actors and their roles; a description of the potential benefits for the various business actors; a description of the sources of revenues"
2001	Amit & Zott	The business model depicts "the content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities"
2002	Chesbrough & Rosenbloom	The business model is "the heuristic logic that connects technical potential with the realization of economic value
2002	Magretta	Business models are "stories that explain how enterprises work. A good business model answers Peter Drucker's age old questions: Who is the customer? And what does the customer value? It also answers the fundamental questions every manager must ask: How do we make money in this business? What is the underlying economic logic that explains how we can deliver value to customers at an appropriate cost?"
2005	Morris et al.	A business model is a "concise representation of how an interrelated set of decision variables in the areas of venture strategy, architecture, and economics are addressed to create sustainable competitive advantage in defined markets"
2008	Johnson, Christensen, & Kagermann	Business models "consist of four interlocking elements, that, taken together, create and deliver value"
2010	Casadesus-Masanell & Ricart	"A business model is . . . a reflection of the firm's realized strategy"
2010	Teece	"A business model articulates the logic, the data and other evidence that support a value proposition for the customer, and a viable structure of revenues and costs for the enterprise delivering that value"

Table 2. Selected overview of BM definitions. Adapted from: Zott, Amit & Massa (2011)

2.2 Conceptualizing Business model innovation (BMI)

As demonstrated, BM is a highly complex concept making it difficult for scholars to reach consensus on what constitutes to a BM and what does not. These difficulties are only further aggravated when the discussion involves changes in BMs. For example, what type of changes are considered as BMI? What number of changes is sufficient to be labelled BMI? How are they implemented and evaluated? These questions, among others, are still under debate and have resulted in conceptual ambiguity in the literature (Saebi et al., 2017).

Two overviews of BMI literature

The literature on BMI found its origin about two decades ago and has been steeply increasing ever since. According to Foss and Saebi (2017a), the current literature can be classified into four different research streams (Figure 5).

First, there is a group of scholars that discusses the phenomenon itself and debates about the minimum meaningful definition of BMI. Especially what is, and what is not BMI, and to which dimensions a firm can innovate its BM is still a question that is being under the scanner. Amit and Zott (2012) think of BMI as a new source of innovation that "complements the traditional subjects of process, product and organizational innovation". Using different terminology, Foss and Saebi (2017) define BMI as "designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements". Over the years, different definitions have been proposed (Table 3). A second stream of BMI research focuses on BMI as an organizational change process. Following this perspective, BMI is considered as process involving different phases. Capabilities that enable change and practitioner-oriented tools are being discussed that facilitate the process of BMI. A third stream focuses on the outcome of BMI, by elaborating on examples of innovative BMs in a certain context. Herein, mostly the adoption of new BMs in specific industries is presented in descriptive works. Fourth, there exists a stream of research that addresses the effect on organizational performance of BMI. At a general level this can be done either indirect, by linking different types of BMs to firm performance, or direct, by linking activity in the process of BMI to outcome.

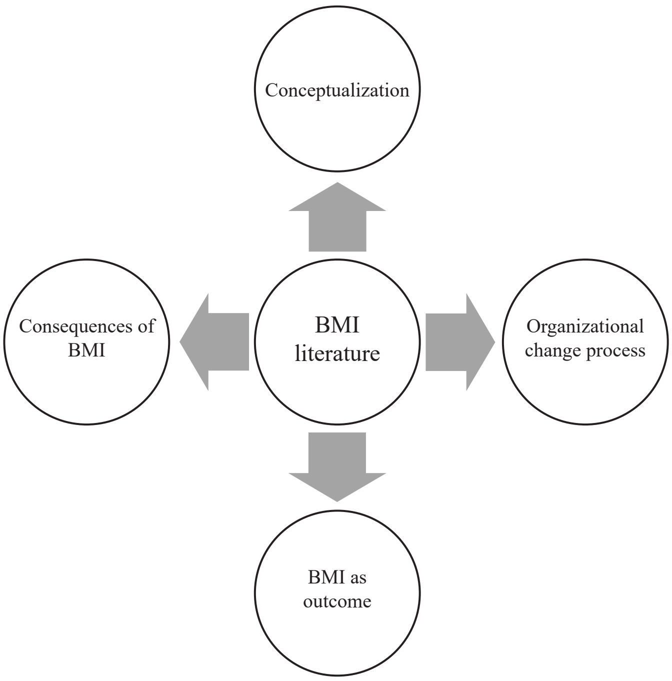


Figure 5 Four research streams in the BMI literature according to Foss and Saebi (2017).

Wirtz et al. (2016) have a slightly different characterization of the literature and distinguish six research areas (Table 4). Research areas with a conceptual focus concern BMI definition, types and frameworks to unbundle the concept. Similar to the classification of Foss and Saebi (2017b), they identify an area considering BMI as a process. From the six research areas listed, the area about BMI design and process is the largest, representing roughly one fourth of the current literature (Wirtz et al., 2016). Studies in this area conceptualize BMI as "an additional method for innovation"(Wirtz et al., 2016), an "act" (Foss & Saebi, 2017b), or "practice" (Molina et al., 2017), that can be an effective tool to innovate the firm's activities

(Amit & Zott, 2012). Then there exists a group of work about the drivers and barriers of BMI. Here, factors are studied that drive or hamper adoption of BMI practices. From a more practical-oriented lens, scholars study how BMI should be implemented by managers and what measures can be developed to evaluate BMI feasibility.

Year	Author	Definition
2004	Mitchell and Coles	"By business model innovation, we mean business model replacements that provide product or service offerings to customers and end users that were not previously available. We also refer to the process of developing these novel replacements as business model innovation."
2006	Markides	"Business model innovation is the discovery of a fundamentally different business model in an existing business."
2009	Santos et al.	"Business model innovation is a reconfiguration of activities in the existing business model of a firm that is new to the product service market in which the firm competes."
2010	Aspara et al.	"Initiatives to create novel value by challenging existing industry specific business models, roles and relations in certain geographical market areas."
2010	Gambardella and McGahan	"Business-model innovation occurs when a firm adopts a novel approach to commercializing its underlying assets."
2010	Yunus et al.	"Business model innovation is about generating new sources of profit by finding novel value proposition/value constellation combinations."
2011	Sorescu et al.	"As a change beyond current practice in one or more elements of a retailing business model (i.e., retailing format, activities, and governance) and their interdependencies, thereby modifying the retailer's organizing logic for value creation and appropriation."
2012	Amit and Zott	Innovate business model by redefining (a) content (adding new activities), (b) structure (linking activities differently), and (c) governance (changing parties that do the activities).
2012	Bucherer et al.	"We define business model innovation as a process that deliberately changes the core elements of a firm and its business logic."
2013	Abdelkafi et al.	"A business model innovation happens when the company modifies or improves at least one of the value dimensions."
2013	Aspara et al.	Corporate business model transformation is defined as "a change in the perceived logic of how value is created by the corporation, when it comes to the value-creating links among the corporation's portfolio of businesses, from one point of time to another."
2013	Berglund and Sandström	"A BMI can thus be thought of as the introduction of a new business model aimed to create commercial value."
2013	Casadesus-Masanell and Zhu	"At root, business model innovation refers to the search for new logics of the firm and new ways to create and capture value for its stakeholders; it focuses primarily on finding new ways to generate revenues and define value propositions for customers, suppliers, and partners."
2014	Khanagha et al.	"Business model innovation activities can range from incremental changes in individual components of business models, extension of the existing business model, introduction of parallel business models, right through to disruption of the business model, which may potentially entail replacing the existing model with a fundamentally different one."

Table 3. Selected overview of BMI definitions. Adapted from: Foss and Saebi (2017)

As overviewed, BMI attracts attention from various scholars and is studied in different research areas. BMI is a concept that is not trivial to measure, since it is linked to the organization in many and complex ways. To measure BMI in an empirical way, dimensions need to be identified. The concept BMI has multiple aspects and various dimensions have been proposed that provide use for valid measurement of BMI.

Research area	Key content
Definition & Types	Basic definition of BMI concept and differentiation from existing concepts Differentiation of certain BMI types
Design & Process	Ex-ante BMI development Steps and phases of BMI
Drivers & Barriers	Drivers of BMI Barriers of BMI
Frameworks	Unbundling of BMI concept Categorization of concrete parameters
Implementation & Operation	Arrangements for BMI implementation Running BMI business operations
Performance & Controlling	Ex-post measurement of BMI feasibility, profitability, and sustainability

Table 4. Six research areas of BMI, adapted from Wirtz et al. (2016).

Central BMI dimensions

Recently, different BMI dimensions have been overviewed and linked in an integrative conceptual framework (Wirtz & Daiser, 2017)(Figure 6). Some scholars focus on the intensity of BMI, and map these along a spectrum of impact varying from changes that affect a part of the organization, or the organization as a whole, to changes that are new to the industry, or that are focused on complete new market segment (Zott & Amit, 2008). Other scholars focus on the type of BM components as dominant dimension, by which they mean which and how many BM components are affected by a BMI (e.g. Frankenberger et al., 2013; Lindgardt et al., 2009). This discussion involves the question as to how many components are sufficient or necessary for a change to be attributed as BMI. As mentioned, another distinction can be made between scholars who study BMI as an outcome and scholars that see BMI as an organizational process.

Taken this, it may be clear that different ways exist by which BMI can be conceptualized and operationalized. Each approach can have its own advantages and shortcomings, and therefore, researchers should deliberately consider the options depending on research context and objective.

We argue that, compared to studying BMI as an outcome, a conceptualization of BMI as a process provides more relevance for managers and policy makers. In this study, the objective is to investigate the causal effect of BMI engagement on firm performance. When performance implications are evidenced by means of a process-oriented conceptualization, there is an opportunity to enhance performance of firms that are currently not engaged in BMI practices. Hence, our study conceptualizes BMI is as a process and falls in the group of studies that link activity in the process of BMI to firm performance. Against this background, we follow Massa and Tucci (2013) and define BMI "as the activity of designing—i.e., creating, implementing and validating— a new BM".

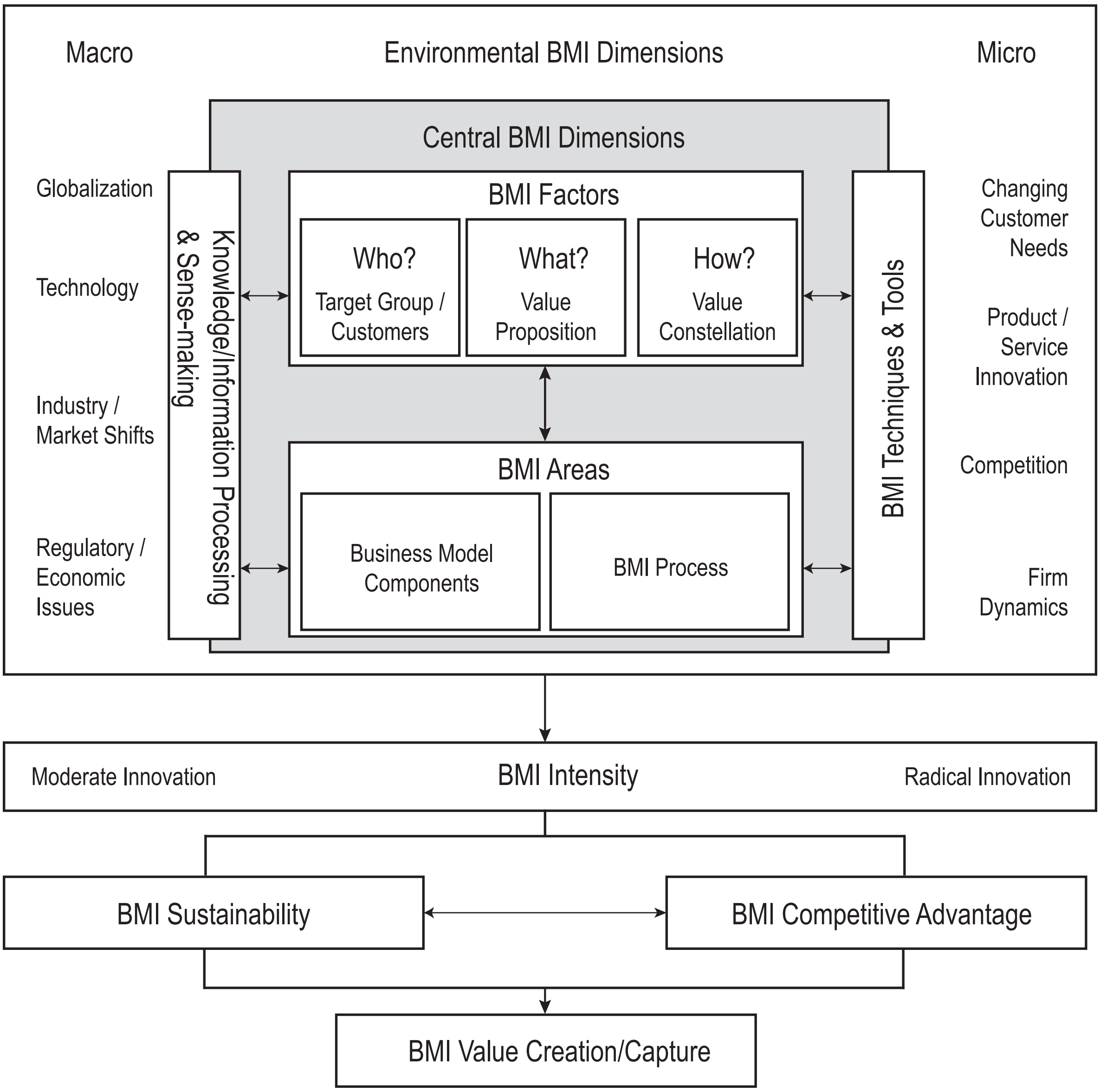


Figure 6 Different dimensions of BMI. Adapted from Wirtz & Daiser (2017).

BMI as a process

Scholars studying BMI as an organizational process tend to approach BMI as an additional method for innovation (Sinfield et al., 2012; Wang et al., 2015). In this regard, BMI design has been argued as effective tool to innovate a firm's activities (Zott & Amit, 2007). Some studies focus on the process of developing a BM from a start-up perspective (e.g. Geissdoerfer, Savaget, & Evans, 2017), while others focus on changes in incumbent BMs (e.g. Ahuja & Novelli, 2016; Kim & Min, 2015). Following this later group, our study views BMI as organizational process that firms use to innovate their existing BM. Because of the increasingly dynamics business environment, firms are obligated to continually rethink and enhance their BM (Huang et al., 2013). Therefore, BMI may not be single act of change but rather a continuous process that companies should invest time and resources in (Giesen et al., 2010).

While various scholars agree on considering BMI as active process, there is little consensus on how this procedure should further be conceptualized. Most of the studies describe distinct phases, but others have argued that in practice these activities coexist and that BMI should be regarded as trajectories rather than process of multiple phases (Berends et al., 2016). Relatedly, there is still debate on whether BMI comes about through cognition, action or both. Those supporting the view that cognition is the driving source of BMI, believe in a forward-looking process, in which models are conceived first before implemented in practice (e.g. Aspara, Hietanen, & Tikkanen, 2010a). On the contrary, supporters of a dominant role of action assume a backward-looking approach, in which experiences compete to become routinized actions (e.g. McGrath, 2010). In reality, these approaches may be used simultaneously or in an iterative process (Berends et al., 2016). However, in empirical studies, an ambiguous approach is often not feasible because of the complexity it raises in operationalization. Our study considers BMI as forward-looking, learning process, in which experimentation forms the basis for implementation activities. While this may be a simplification from reality, we argue this approach is worth investigating, mostly because this aspect of BMI can be easily promoted in practice. Compared to a backward-looking process, a forward-looking process is tangible and can be stimulated by promoting activities involved in this process. Therefore, this direction can be of special interest for policy makers and managers. Within the group of scholars that pursue this forward-looking approach, different conceptualizations have been proposed (Table 5).

Some scholars conceptualize BMI as linear process. Enkel and Mezger (2013) distinct a design phase from implementation and Geissdoerfer et al. (2017) add another phase to separate concept design from detail design. Linder and Williander (2017) stress the importance of circularity in BMI and link distinct phases in a circular way. Relatedly, Mentink (2014) proposes a circular BMI (CBMI) framework consisting of four different phases: initiation, ideation, integration, and implementation.

A different group assumes a semi-structured approach to guide the process of BMI. This can involve questioning techniques and experimental trial-and-error loops (Wirtz et al., 2016). In this regard, Hoveskog et al. (2015) argue the need for active experimentation, and propose the use of the nine elements of business model CANVAS as experimenting template. Sinfield et al. (2012) present clear questions that may be used to guide the creative process of BMI. Günzel and Holm (2013) divide BMI in two innovation activities, which they refer to as front-end and back-end BMI and argue the need for a mixed approach. While back-end BMI, i.e. internally-oriented, may be structured by means of a linear approach, front-end BMI that originates from external changes may need an experimental trial-and-error approach. Then there are scholars who focus on methods and tools that facilitate the process of BMI (e.g. ENVISION, 2016; Eppler & Hoffmann, 2012). This involves tools to evaluate the feasibility of BMs and creative methods that can be used for systematic idea generation.

In sum, various ways exist by which the process of BMI can be conceptualized, and authors have stressed different points in need of special attention. In general, however, two phases seem to reoccur in most of the work: (1) a design/experimentation phase, that is followed by (2) a phase of implementation/execution. In this study, we simplify the process of BMI by focusing on BMI engagement, which we define as composite of BM experimentation and BM implementation.

As examined, the relation between such phases have been discussed in different ways. While some assume a linear approach, others argue they coexist or intertwine and some argue they are encompassed by one complex concept. While it may in general be true that experimentation precedes implementation, it may be too simple to assume a linear approach. Firms who actively engage in experimentation can simultaneously be involved in implementation activities. Further, experimentation activities may not directly result in implementation activities, because outcomes of experimentation may not appear fruitful. Therefore, a rather complex interaction between these phases might exist in reality (Figure 7). In general, experimentation can result in implementation. These are activities that happen in the process of BMI. We argue that firms who are actively involved in both can be considered as engaged in BMI.

Key Business Model concepts	Approach	Reference
Design, Implementation	Linear	Enkel & Mezger, 2013
Idea generation, Model articulation, Risk identification and task prioritization, Experimentation	Linear, Stage-gate	Girotra & Netessine, 2013
Six-step approach	Linear	Eurich, Weiblen, & Breitenmoser, 2014
Concept design, Detail design, Implementation	Linear	Geissdoerfer, Savaget, & Evans, 2017
Design, Execution, while considering the "Three As": Aligned, Analytical, Adaptable	Semi-structured	Giesen et al., 2007
Experimentation based on business model CANVAS elements	Semi-structured	Hoveskog, Halila, & Danilovic, 2015
Execution innovation development	Semi-structured	Tuulenmäki & Välikangas, 2011
Experimentation	Semi-structured	Sinfield et al., 2012
Experimentation, in front-end (externally-oriented) and back-end (internally-oriented) innovation	Mixed approach	Günzel & Holm, 2013
Tooling, Idea generation	Method-oriented	Eppler & Hoffmann, 2012
Multi-step, through "Drifting" and "Leaping"	Learning trajectories	Berends et al., 2016

Table 5. Selected overview of studies addressing BMI as process.

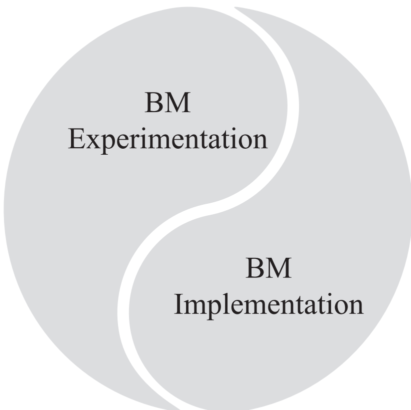


Figure 7. BMI Engagement.

2.3 BM Experimentation

The aim of BM experimentation can be to learn and improve BMI activities. In addition, experimentation can result in several benefits for the firm. Bocken et al. (2018) found that experimentation stimulates engagement to start with business transitions and helps to evaluate established business components. In similar lines, Chesbrough (2010) argues that these practices reduce barriers for business model change and help to take away confusion. Christensen (1997) stresses the importance to allocate resources to new innovative projects with new experimenting BMs leaving the core business of the company unaffected. Successful experimentation can result in identification of new, fruitful BMs. In turn, innovative

BMs contribute to competitive advantage and firm performance (Zott & Amit, 2007), which is a clear motivation for companies to start with experimentation.

Despite this attractiveness, experimentation is associated with different challenges and is prone to failure (Pauwels & Weiss, 2008). One of these challenges comes from the complexity of evaluating the effectiveness of new BMs (Andries & Debackere, 2006). Since BMs consist of multiple components that have strong interactions, single components cannot be considered in isolation. It remains therefore a complicated task to estimate the effect of changing and reconfiguring certain BM components. For established firms, this challenge is even further complicated because they need to develop a new BM in parallel with their existing BM (Mezger, 2014). Established firms can innovate from their existing model which can provide synergies but also cause conflicts between the new and old model.

Considering these challenges, it may be clear that experimentation of BMs is an attractive but difficult task. So how do business experiment with their BMs in practice? Obviously, this question cannot be answered unequivocally, and an answer may depend on the industry and characteristics of the firm.

In contrast to experimentation in natural sciences, business experimentation cannot benefit from controlling and manipulating certain variables of the business model, as businesses deal with processes that cannot be readily halted. Business model experimentation aims to explore diverse possibilities – by innovation and reconfiguration of existing BM components, that could create value for the business (Bocken et al., 2018). Because of the challenges mentioned, accurate evaluation a priori remains difficult and experimentation, therefore, can be seen as a long-lasting trial-and-error process (Sosna, Trevinyo-Rodríguez, & Velamuri, 2010). In addition, experimentation requires rapidly testing and correcting assumptions in time, so that the initiative is driven toward beneficial outcome (Blank, 2013).

In practice, distinct approaches are used and therefore different ways exist by which BM experimentation can be defined, conceptualized and studied. Albeit these differences, Baden-Fuller & Morgan (2010) argue the common denominator is that BM experimentation involves both thought experiments, and real-life experiments. In this study, we follow the view that experimentation comes from a purposive effort that may result in both type of experiments. Hence, we point out the need to allocate budgets for experimentation, an activity that may be practiced by a specific team assigned to the task. In turn, these efforts can lead to the identification of opportunities that seem fruitful for BMI, and that can evolve into efforts of BM implementation.

2.4 BM Implementation

The experiments may lead to new BM designs, but to benefit from this design, the novel BM should be put into practice. Whether an intended BM can actually be realized depends on the alignment between the BM and the business processes (Lueg, Malinauskaite, & Marinova, 2014; Solaimani, 2014). Where BMs describe what the firm should do to create value, the how-question is addressed during the implementation of the BM (Bouwman et al., 2008).

BM implementation is highly dependent on the operational business activities and processes at various organizational levels (Bask, Tinnilä, & Rajahonka, 2010; Bouwman et al., 2008), which together have been referred to as Business Operation (Gordijn, Akkermans, & Van Vliet, 2000). These activities are complex and strongly depend on the context of the firm (Solaimani, 2014).

We aim to capture the activity of BM implementation in changes in the Business Operation. In the literature, these processes have been described in different ways. Two main research streams that aim at understanding these operations concern: Business Process Management (BPM) and Enterprise Architecture

(EA) (Solaimani, 2014).

The research on BPM includes various approaches and techniques designed to analyze and improve (Lin, Yang, & Pai, 2002), automate and innovate businesses processes (O'Neill & Sohal, 1999). Several scholars have developed BPM modeling techniques to facilitate these actions, such as Petri nets (Murata, 1989), Unified Modeling Language (Fowler, 2004) and Business Process Modeling Notation (Object Management Group (OMG), 2011). In contrast to large scale organizations, which have widely recognized BPM software tools, SMEs have not drawn much attention in this regard (Karras & Papademetriou, 2017). It has been argued that these tools may be too complicated for most SMEs, and that more practical, simplified tools are needed (Karras & Papademetriou, 2017).

The work on EA concerns the design and realization of the firms' organizational processes, (infra)structure, and systems (Lankhorst, Proper, & Jonkers, 2009). EA has been discussed by Ross, Weill and Robertson (2006): "Enterprise architecture is the organizing logic for business processes and IT infrastructure reflecting the integration and standardization requirements of the company's operating model. The operating model is the desired state of business process integration and business process standardization for delivering goods and services to customers". Originating from a focus on IT, EA has been evolved to a broader, abstract construct that is closely related to the firms' strategy (Malan et al., 2006). In this study, we conceptualize Business Operations as EA and OM rather than BPM because the former is more recognized in the context of SMEs.

The EA interacts with the company's Operating Model (OM) and postulates the organizing logic for business processes and IT infrastructure (Ross et al., 2006). Together, these concepts explain how operational business processes are managed and executed in practice. Changes in these concepts alter the firms' BM and ensure new ideas can be implemented on to the existing BM.

As described by Ross et al. (2006), the complex relation between EA, OM and strategy can be considered as cyclic. The EA and OM define the limits for strategic initiatives. Strategic initiatives, in turn, help to establish priorities and formulate a foundation for execution. Next, these initiatives will interact with the engagement model, which updates and evolves the EA (Figure 8). In this way, EA and OM, as representation for the process of BM implementation, will interact with the strategy via the BM.

Operating Model

The Operating Model describes how the firm aims to thrive and grow. According to Ross et al. (2006), "the operating model is the desired state of business process integration and business process standardization for delivering goods and services to customers". They serve as critical link between strategy and detailed organizational design.

At a general level, Operating Models can be classified depending on their focus on standardization and integration respectively (Ross et al., 2006). With an increasing need for standardization, Operating Models tend to evolve from diversification to replication, providing standards for business units that operate in similar ways (Ross et al., 2006). With an increasing need for integration, Operating models become more focused on coordination, facilitating data exchange between business units.

Operating Models exist of a composition of elements that work together to support the company's goals. Examples of these elements include a description of superstructure, how the profit and loss statement maps to the main business units, and formulation of accountability, where and how decisions are made (Rousseau, Montaville, & Videlaine, 2012).

An often-observed challenge is to keep the operating model aligned with the Business Model (Solaimani, 2014). Given that the Operating Model fulfils a crucial role in the implementation of the Business Model, it should interact and adapt to the changes made in the Business Model. For this reason, it is often advised to companies to allocate resources to manage the operating model and provide a description of each element within the operating model (Ross et al., 2006).

However, for SMEs this is not always feasible or appropriate, as they operate in a context with less resources. Yet this does not imply that Operating Models are just reserved for large companies. Operating Models can exist along a continuum based on the desired complexity. For small organizations a poster or graphic could provide the mission vision values and process capabilities. Independent from its complexity, defining and aligning an Operating Model can be a fruitful investment as it could avoid unnecessary issues and may lead to positive changes in the organization (Murphy, Kirwin, & Abdul Razak, 2016).

Given the focus on SMEs, this study will define Operating Models as bridge between strategy and "what you do on a daily basis" (Molina et al., 2017). The following components are used to address this in the context of SMEs: standards for how products and services are delivered to customers; division of work between enterprise and partners; ways to manage cost and execute processes; arrangement of organizational structures.

Reference	Study	C(N)	BMI construct	Modeling type
Aspara et al., 2010b	CS	1	Strategic emphasis on BMI	Sum of responses
Bock et al., 2012a	CS	1	BMI effort	Single indicator
Hock et al. 2016	CS	1	Propensity for BMI	1st order Reflective
Brea-Solís et al., 2015	LG	8	BM levers (BM implementation)	Proxies from available secondary data
Velu, 2015	LG	1	The degree of BMI	Expert validation to assign firms in categories of BMI activity
Kim & Min, 2015	LG	1	Incumbent BMI	Proxies from available secondary data
Cucculelli & Bettinelli, 2015	LG	1	BM change	Classification of BM changes by innovation (low, medium, high)
Gronum et al., 2016	CS	2	Innovation breadth BM design themes (Novelty, Transaction efficiency, User simplicity)	Classified according to business model elements 1st order Reflective
Clauss, 2017	CO	1	BMI	3rd order Formative
Molina et al., 2017	CS	2	BMI design BM experimentation	1st order Reflective 1st order Reflective
Current study	CS	2	BM experimentation BM implementation	1st order Reflective 2nd order Reflective

Table 6. Examples of empirical studies that relate BMI to outcome implications. CS: cross-sectional; LG: longitudinal; CO: conceptual; C(N): constructs used for BMI operationalization.

Enterprise Architecture

Like the Operating Model, the Enterprise Architecture plays a role in the implementation and execution of the Business Model. Where the Operating Model revolves around the translation of operational strategy, the Enterprise Architecture has its focus on implementation of a technical strategy. In distinction to the Operating Model, Enterprise Architecture has been defined as "the organizing logic for business processes and IT infrastructure, reflecting the integration and standardization requirements of the company's operating model" (Ross et al., 2006).

The definition of Enterprise Architecture has been evolving in the literature, increasing its significance and applicability in different disciplines (Malan et al., 2006). Early work was focused on Technology Architecture, establishing technology standards and principles. Zachman was one of the pioneers and defined EA as "a logical construct for defining and controlling the interface and the integration of all of the components of the information system" (Zachman, 1987). The concept gained broader applicability when EA was being addressed as Enterprise-wide IT Architecture, including Information and Application Architecture. Later, the definition was further extended with the inclusion of the Business Architecture, which gave EA a multidisciplinary scope that gained overlap with related strategic concepts (Malan et al., 2006).

In parallel with the conceptual evolution of EA and stimulated by the growing importance of technology, EA frameworks have been developed with increasing complexity. Because of the detail required for full-scale implementation, current EA models tend to become very large (Bernaert et al., 2016). While large organizations have the resources to assign specialists or hire external consultants, for SMEs this might be less obvious. Moreover, since they are not aware of the options or perceive the EA frameworks as too complex, SME managers might be restrained from investing in EA frameworks (Bernaert et al., 2016). As a result, the models discussed in the literature are rarely used by SME managers. Accordingly, evaluation of EA based on existing frameworks provides little use in the context of SMEs. Instead, we follow the view from Ross et al. (2006) and conceptualize EA on a higher level of abstraction concerning its different aspects: business processes and structure; business process standardization and integration; internal controls to monitor processes; ICT, application and infrastructure.

2.5 BMI and firm performance

While there is growing support for the claim that BMI promotes firm performance (Foss & Saebi, 2017; Wirtz et al., 2016), the amount of empirical research proving this relation remains limited. In general, scholars who study consequences of BMI can be separated in two groups. There is a group of scholars that test the effect of different BM designs on innovation performance. In this group, scholars explore dimensions that differentiate BM designs. For example, Zott and Amit (2008) found a positive relation between novelty-focused BMs and firm performance. In the other group, scholars link the act of BMI to outcome implications. These studies generally assume a process view of BMI and investigate whether bringing changes to the existing BM results in superior performance. This study builds on the work of this latter group, as we investigate the effect of BMI engagement on firm performance.

Among those studies that follow the view of BMI as act, great differences exist on how BMI has been conceptualized and modelled (Table 6). Aspara et al. (2010b) measured BMI based on two indicators and found that strategic emphasis on BM innovation or replication supports profitable growth of the firm. In addition, they report that for small firms the strategic emphasis on BM innovation outweighs the emphasis on replication in terms of profitable growth. Hock et al. (2016) used three indicators to capture the propensity for BMI and found that novelty-oriented cultural values foster capabilities enabling BMI. Bock et al. (2012a) used a single indicator to capture BMI effort, and found a moderating effect of BMI on strategic flexibility. Gronum et al. (2016) distinct BMI efforts on the extent of novelty and found enhanced performance effects only when efforts where focused to novelty and efficiency. Molina et al. (2017) separate BMI in two phases of BMI design and BM experimentation and found a positive effect on innovativeness and firm performance.

Ideally, a longitudinal approach would be favourable as it enables to follow performance implications in time. However, it remains difficult to collect sufficiently detailed information on BMI along a temporal dimension. Although some studies pursue a longitudinal approach, they rely on proxies form available secondary data (Brea-Solís, Casadesus-Masanell, & Grifell-Tatjé, 2015; Kim & Min, 2015) or afterwards expert validation (Velu, 2015). Brea-Solís et al. (2015) found that effectiveness of a BM depends not only on its design but most importantly, on its implementation. Velu (2015) found that firms with a high degree of BMI are more likely to survive than firms with a moderate degree of BMI. Kim and Min (2015) show that timing and organizational model play a role in the success of adding BM changes, which in turn results in improved performance.

Taken this, the question as to how BMI contributes to performance is raising attraction from different scholars. Since BMI such a challenging construct to measure, different approaches have been used to capture the concept. Albeit these differences, these examples provide corroborative evidence for the argument that BMI can be a valuable concept that can contribute to the firm's performance in different ways.

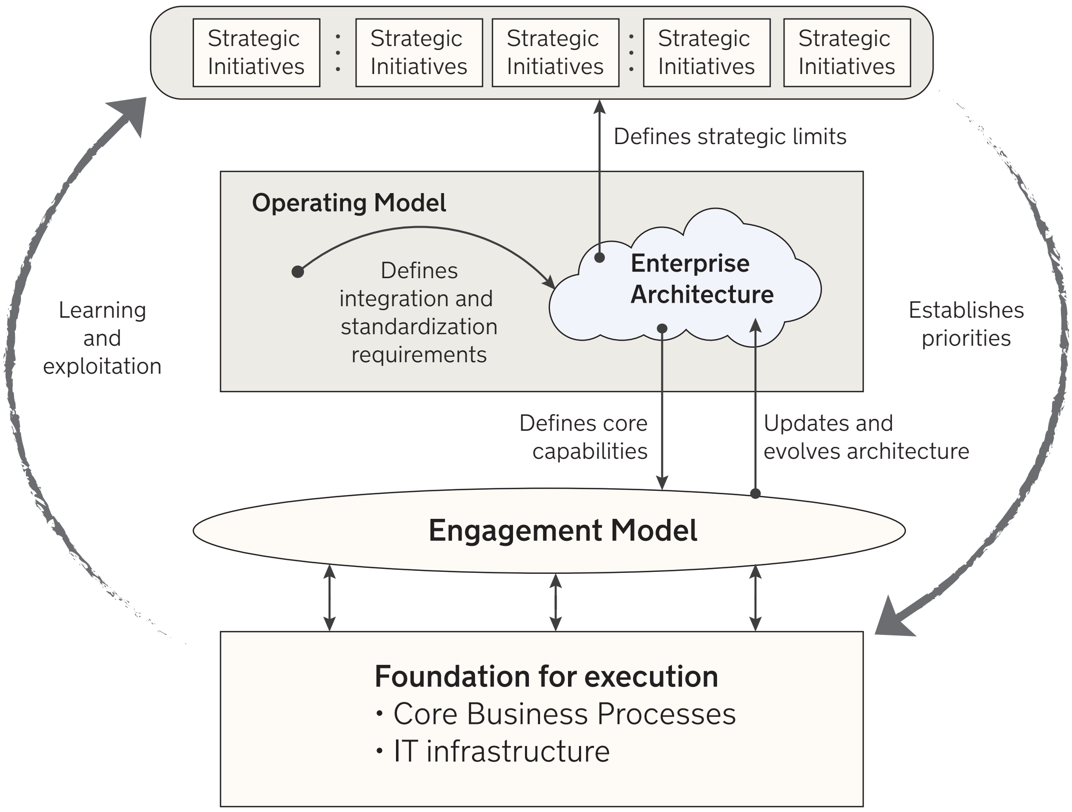


Figure 8 Link between enterprise architecture, operating model and strategy (Adapted from Ross et al. 2006).

2.6 BMI in SMEs

The context of SMEs is novel for BMI research and few studies have made use of empirical surveys on BMI (Bouwman et al., 2017). In SMEs, BMI practices can differ considerable compared to the context of large corporates. This raises the question to what extent BMI research and models can be mirrored to SME context and to what extent unique features of SMEs are sufficiently captured (J. Heikkilä & Heikkilä, 2017).

SME managers might not be aware of existing tools and frameworks that could guide them in the process of BMI. Most SMEs, therefore, use the help of external consultancy firms or researchers when applying BMI methods to their BM (Bouwman et al., 2017).

Although about one third of the SMEs is engaged in BMI activities, few of them do so in a systematic manner or acknowledge these activities as BMI (Molina et al., 2017). Since SMEs might not have an explicitly formulated strategy, they may follow rather heuristic approach compared to the more purposive approach in larger firms. Heikkilä et al. (2017) suggest that strategic goals of the SME determine the BMI path, in which sequential, non-linear and iterative steps are taken to improve specific BM components. Relatedly, J. Heikkilä and Heikkilä (2017) link BMI to bricolage and new product development, the combination of which they argue reflects reality most well. These examples highlight the need to encounter SME-specific factors when studying BMI.

While smaller companies have more internal flexibility and adaptive capabilities compared to large firms, this does not imply that complex changes such as BMI are easily done (M. Heikkilä et al., 2016). SMEs often have less resources that can be allocated to specific tasks such as BMI, which hampers SMEs from realizing potential opportunities. Guo et al. (2017) found that BMI mediates the effect of opportunity recognition on performance in SMEs, which stresses the importance of BMI for SMEs. Recently, Anwar (2018) provided evidence for a positive impact of BMI on SME performance.

In sum, despite the lack of sophistication, BMI is on the way to reach mainstream in SMEs (M. Heikkilä et al., 2016). Although SMEs draw the attention from various scholars in innovation literature, BMI in SMEs is still far from being fully understood. Novel research is needed to verify the applicability of BMI models on the SME context and to investigate differences in further depth.

2.7 Conclusion

Complex phenomena can be studied in different ways and there exists no single manner that provides optimal use for all contexts. This Chapter introduced the complexity involved in defining Business Models and showed how this complexity is increased when changes in BMs are being investigated.

We argued to follow the idea that BMI can be described as organizational learning process consisting of different phases, a view that has been conceptualized in various ways. From the various conceptualizations available, we selected two distinct but reoccurring concepts to represent BMI engagement: BM experimentation and BM implementation.

Focussing on the consequences of BMI, an overview of the current literature was presented. Here, we answered sub question one by listing the diversity of measurement approaches and conceptualizations currently available.

Finally, we touched upon some novel BMI research in SMEs. This context complicates some prior assumptions since findings from larger corporates may not directly apply to the context of SMEs. During operationalization, as will be discussed in Chapter 4, this notion deserves special attention. In the next Chapter, the research model will be presented together with the hypotheses and conceptual model.

Chapter 3 Research model

The previous Chapter argued that BMI engagement can be considered as the extent to which firms are involved in BM Experimentation and BM Implementation. Our study aims to investigate the relation between BMI engagement and business performance. In this Chapter, the relations between these concepts will be discussed and used to develop a research model. Hypotheses will be presented and combined in conceptual models.

3.1 Perceived business performance

As discussed in Chapter 2, BMI can have multiple beneficial consequences such as contributing to sustainability and competitive advantage. The complexity by which BMI interacts with the multiple beneficial outcomes provides interesting questions in need of further research but lay beyond the scope of this study. This study involves one dependent variable: business performance. Business performance is a challenging outcome to study given the severe number of factors that can influence this variable. Nevertheless, positive relations with this construct come with great managerial relevance which makes firm performance an interesting dependent variable for empirical studies.

Business performance can be studied along different dimensions that could be fruitful for BMI studies. For example, customer performance, market performance and financial performance comprise different criteria that can be influenced by BMI. However, since our data contains a very heterogenic set of firms, which can practice BMI in various ways, we choose to focus solely on financial criteria as measure for business performance.

Furthermore, the heterogeneity of our population makes it difficult to directly compare financial numbers across companies. The industry in which a firm operates can strongly influence the observed financial criteria. Even at a relative level, great differences can be observed in financial ratios, which make it difficult to detect subtle changes. To accommodate with this, we study perceived business performance, where measures for financial growth rely on the managers' evaluation of the financial situation.

The advantage of using indicators that rely on perception is that numbers can be compared and that no outliers exist that may disturb results. In addition, historical growth may be included in managerial perceptions while this information cannot be identified from financial rations of one year. However, the use of perceived business performance has its own limitations. Most obviously, results from these indicators do not directly represent financial indicators, and findings must be evaluated with this in mind. Next, there may be factors that influence managerial perceptions. Researchers may find a causal relation while in reality there exists a spurious relation that can be explained by factors influencing managerial perceptions. These limitations and ways to evaluate their effect will be discussed in Chapter 4.

3.2 The role of firm characteristics

As presented in Chapter 1, this study will focus on four structural firm characteristics: firm age, size, gender of CEO, and family versus non-family enterprise. Below, motivation will be given the selection of these characteristics and two potential roles of firm characteristics will be discussed.

From a policy perspective, it is useful to investigate firm characteristics that are tangible, and easily observed. Whenever effects are identified, policy makers may want to use these findings to tailor their actions to parts of the population. Hence, ownership characteristics (gender of CEO, family enterprise) and firm characteristics (size, age) are easily observed and are useful in this regard. Furthermore, these characteristics have been studied in innovation literature, which support the selection form a theoretical view.

Gender-based differences may be caused from differences in risk aversion (Zeng & Wang, 2015) or entrepreneurial orientation (Bae, Chang, & Kang, 2012). Firm size can influence the availability of resources and the firm's momentum (Ruzzier & Ruzzier, 2015). Differences between family and non-family firms can arise from educational differences of the CEO, or from differences in management training activities (Smith, 2007). Aging could result in organizational rigidities, but could also support activities in planning and control (Loderer & Waelchli, 2011).

These examples demonstrate the complicated relations that these characteristics may have on certain practices. Often, characteristic-dependent effects are not straightforward, and bring both advantages and limitations. Nevertheless, these characteristics can severely influence business processes, which is why the effect of characteristics is investigated in different contexts. In the context of BMI, these characteristics have been mildly investigated.

Hartmann et al. (2013) show that firm size moderates the effect of BMI on operational performance and that larger firms are better able to exploit opportunities of BMI. Bouncken and Fredrich (2016) find that larger firms tend to experience more moderate financial benefits from BMI compared to smaller firms, which experience more extreme effects. Moreover, they show that younger firms experience more drastic effects on financial outcome than firms with advanced age. Furthermore, gender of CEO has been found to effect drivers of BMI, but its impact on BMI outcomes was found insignificant (Molina et al., 2017).

In sum, these characteristics can influence the models in different ways. This study will address the role of firm characteristics in two ways. First, by SEM analysis an exploratory approach will be used to identify the moderating effect of these firm characteristics on BMI engagement. A clarification on their moderating role can help to nuance results and to identify differences in the relations of the models. Second, by LCA and fsQCA an exploratory approach will be pursued to address the direct effect of these firm characteristics. This provides insights on how characteristics explain differences in the level of BMI engagement.

3.3 Conceptual Model SEM

The causal relations between the constructs will be assessed during the SEM analysis. Theoretical reasoning is the basis for a conceptual model that serves as input for this analysis (Figure 9). In this section, hypothesis will be presented and substantiated with literature.

Relation between OM and EA

Within the phase of BM implementation, we denoted two concepts of importance that interact with each other: OM and EA. These concepts have a partial overlap because of their similar role in the process of implementing BM changes.

As argued by Ross et al. (2006), the OM defines the integrations and standardization requirements that serve as input for how the EA is formed. The EA postulates the core capabilities that guide further execution of the Business Model. Hence, the OM defines requirements that serve as input for the EA. Following this view, we expect that:

H1: Changes in the Operating Model lead to changes in the Enterprise Architecture.

BM Experimentation and firm performance

BM Experimentation is an important aspect of BMI and can result in new initiatives for BM changes. BMI can allow firms to redefine their core business logic and identify new business opportunities (de Reuver et al. 2009; Osterwalder et al., 2005). Therefore, the relationship can be hypothesized as following:

H2: BM Experimentation leads to firm performance.

BM Experimentation and BM implementation

Interestingly, while the process of BMI has been conceptualized by various approaches, little evidence has come from quantitative studies supporting the idea of distinct phases. In this study, BM experimentation is considered as activity that functions as source for BM implementation.

Previous studies on BM experimentation suggest that these efforts may lead to changes in BM. Activity in BM experimentation can help to reduce barriers for BM change (Chesbrough, 2010). Likewise, actual changes in the BM are often preceded by a prolonged phase of experimentation (Sosna et al., 2010). BM experimentation, therefore, can serve as intermediate step toward realizing a new BM (McGrath, 2010). Consequently, we hypothesize that:

H3a: BM Experimentation leads to changes in the Operating Model.

H3b: BM Experimentation leads to changes in the Enterprise Architecture.

BM implementation and firm performance

Like BM Experimentation, BM Implementation fulfils an important role in the process of BMI (e.g Enkel & Mezger, 2013; Geissdoerfer et al., 2017). Implementation of BM changes enables the firm to adapt and improve the existing BM and can result in beneficial consequences for the firm. Hence, this relationship can be hypothesized as:

H4a: BM Implementation leads to changes in firm performance.

H4b: BM Implementation leads to changes in firm performance.

Strategic initiatives that result from experimentation practices may translate into implementation activities. Therefore, we expect BM implementation to have a positive impact on the outcome of BM experimentation on firm performance:

H5a: Changes in the OM mediate the positive effect of BM Experimentation on firm performance

H5b: Changes in the EA mediate the positive effect of BM Experimentation on firm performance

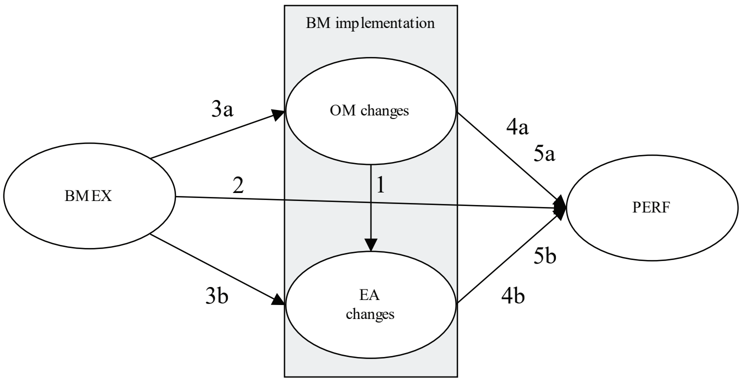


Figure 9 Conceptual model SEM.

3.4 Conceptual model LCA

As discussed in the previous section, firm characteristics may influence the process and outcomes of BMI practices. Apart from their moderating role on these relations, firm characteristics may influence these concepts directly. In the LCA, the direct role of firm characteristics on BMI engagement will be explored (Figure 10).

BMI engagement will serve as variable that encompasses activity in BMI phases (BMEX and BMIM) as well as its association with business performance. Firm characteristics will be added as covariates to study direct effects and compare subgroups in the population.

Using this approach, combinatorial patterns of BMI practices can be classified and overviewed. Here, special focus will be on the effect and comparison between these characteristics. In addition, average engagement in BMI can be compared across subgroups, which may result in valuable insights for policy makers.

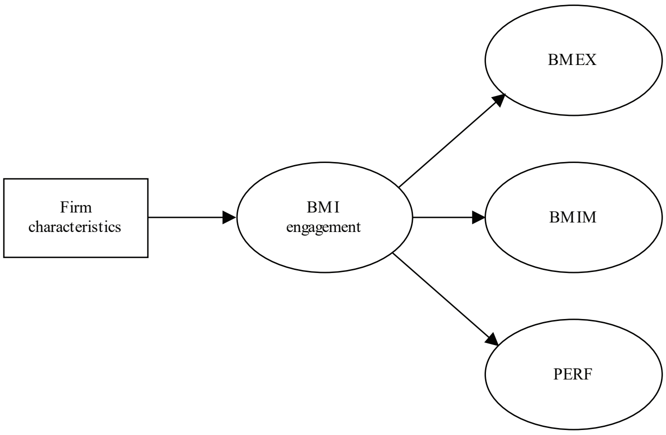


Figure 10 Conceptual model LCA.

3.5 Conceptual model fsQCA

The combined effect of firm characteristics will be explored in the fsQCA (Figure 11). Like the LCA, the fsQCA can be used to study the direct effects of characteristics. While the LCA may be useful to evaluate this regarding cluster size and profile, the fsQCA enables evaluation of multiple firm characteristics simultaneously. Different from the LCA and similar to the SEM analysis, the fsQCA includes a dependent variable. Because of these aspects, this model enables comparison of configurations based on high business performance. Configurations that explain the outcome best will be overviewed and evaluated.

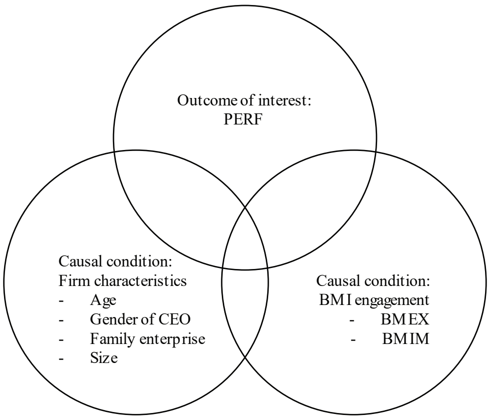


Figure 11 Conceptual model fsQCA.

3.6 Conclusion

This Chapter has introduced the dependent variable and provided motivation for a perceived measurement approach. Elaboration was given on the selection of firm characteristics and two ways were discussed to address their effect. Subsequently, three research models were proposed that can be used to answer the sub questions presented in Chapter 1. Each of these models will be used to deliver insights on a specific issue. Simultaneously, all the models rely on the same concepts and operationalizations, enabling the models to provide corroborative evidence and strengthen each other's findings.

The conceptual model for the SEM was developed based on multiple hypotheses connecting the concepts. In the SEM, a moderating role of firm characteristics on BMI practices will be investigated. Conceptual models for the LCA and fsQCA were presented that enable identification and comparison of direct effects from these characteristics.

Chapter 4 will continue to elaborate on the measurement approach by zooming in on the methodological procedures and assumptions. Argumentation will be given on the operationalizations and measurement models will be analysed and validated.

Chapter 4 Methodology

This Chapter will begin with a description of the nature of the data, how it was collected, and the characteristics of the sample. Then, we will elaborate on the chosen operationalizations for the explanatory models. Subsequently, the measurement model will be presented and validated based on model fitting parameters. Finally, the different approaches to multivariate analyses will be discussed and compared.

4.1 Description of the dataset

In this section, we describe how the dataset we use in this thesis has been developed within the ENVISION project and argue why this data fits as material for analysis.

The data that is used in this study belongs to the H2020 Envision project. The cross-sectional set contains information on BMI from 586 different European SMEs and was collected in early 2016 by a professional research agency with experience in data-collection in multiple countries (Molina et al., 2017).

This dataset matches with the research objectives of this thesis for several reasons. From a policy perspective, the dataset is interesting, since it represents a heterogenic population of firms sampled throughout Europe. Since the data is recently collected, it has a certain representation of the current economic state which provides relevance for European policy makers. From a theoretical perspective, the dataset is interesting too. The large sample size allows for analysis at a level of depth that goes beyond most of the work on BMI. Moreover, the comprehensiveness of the data ensures that all the data needed can be extracted from the dataset, and that no secondary sources are needed to supplement the data.

The used research agency works with native speakers to be able to simultaneously gather data in different European countries. Responses were collected from thirteen different countries across Europe to obtain a representative data set of the European SME economy (Figure 12). Survey responses were collected from the owner or BMI manager of the firm by the use telephone interviews.

A quota was established for micro-, small- and medium-enterprises, to sample them in equal numbers, i.e. tertiles. No quota was set for industry sectors which resulted in a diverse group of firms when classified according to the International Standard Industrial Classification (ISIC, 2013)(Figure 11). Making use of a database from Dun & Bradstreet, companies were randomly selected based on disproportional quota sampling, yielding a final cross-sectional data set with N = 586 respondents.

The questionnaire that has been used to collect the data is included in the Appendix (Supplement A). The list of question is a result of an iterative process with managers and academics that gave input to improve understanding of the questions. Most concepts were measured on seven-point Likert scales (from 1 = totally disagree to 7 = totally agree) and were based on literature on innovation, entrepreneurship and strategic management as indicated. Firms were selected for the study when agreeing to at least one of the four screening questions regarding BM changes (S2A-S2D).

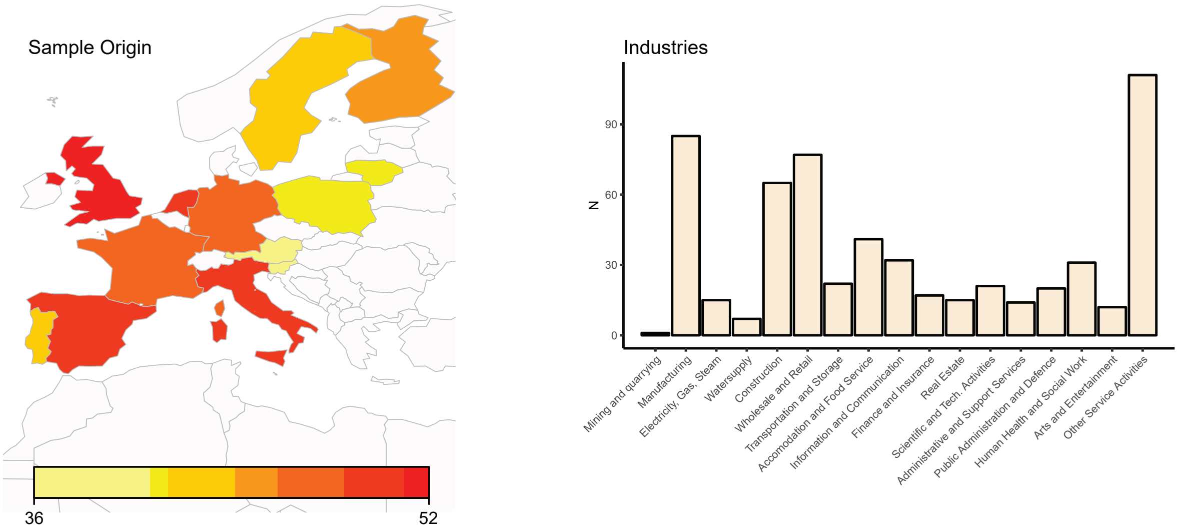


Figure 12 Left: Overview of sampling results per European country. Colors represent the total number of respondents of each selected country in the final data set. Right: Bar plot showing the number of firms in each industry according to ISIC.

4.2 Sample characteristics

The data consist of a sample of 586 SMEs that were included based on screener questions related to BM change. An overview of the firm characteristics and their distribution in the dataset is listed in Table 7.

Surprisingly, most of the SMES themselves did not label the made changes as BMI (61%). Those that did use the terminology BM changes (38%, 1% did not know) were more represented in the medium sized firms (43% made changes), when compare to the small firms (40%) and micro sized firms (30%). While the clear majority of firms had females involved in management teams (74%), about half of the firms had women involved as entrepreneurs of the business (53%) and only a small group had a female CEO (16%). Interestingly, SMEs that were managed by female CEOs reported less changes in their BMs (31%) when compared to group of firms managed by male CEOs (39%). Family enterprises formed most of the sample (56%) and made slightly less frequent changes to their BMs (35%) when compared to Non-family enterprises (42%) (Figure S1A).

The oldest firm was founded in 1836 and the youngest firm was founded in 2016, the year of the data collection, which formed a wide range of firms differing in maturity. While firms were observed at almost any timepoint within these extremes, the bulk was established around 2000, and 1994 appeared to be the median of the sample size, referring to firms that were 22 years old (Figure S1B).

It appeared that firms, especially smaller ones, tend to locate to the lower bound of the size limit, as can be seen from the non-linear shape of the cumulative density distribution (Figure S1C). For example, micro firms with less than five employees were more represented (60%) when compared to micro firms that contained five or more employees (40%).

Firm characteristic			
Size	Micro (35.8%)	Small (33.0%)	Medium (31.2%)
Gender of CEO	Male (83.4%)	Female (15.9%)	Not known (0.7%)
Family enterprise	Family (55.5%)	Non-family (44.5%)	
Age	Median (22 year)		

Table 7. Characteristics of the dataset.

4.3 Operationalization

As pointed out in Chapter 1, this study relies on a dataset that was collected by others. This removes one key feature of ideal operationalization for a researcher: being able to derive measurement dimensions and select aspects out of all suggestions in the literature. The restriction that a predefined dataset brings is that it limits the different options for operationalization. Fortunately, the number of BMI-related items that was collected was sufficiently large to enable different views on BMI. However, in an ideal situation, certain aspects may be added that were not present in the current dataset. This point will be further addressed in Chapter 6.

Latent variables

Based on the conceptual model presented in Chapter 3, Table 8 provides an overview of items used for construct operationalization. For the latent variables, all constructs were measured as multi-item reflective latent constructs. The items used to load these constructs used seven-point Likert scales, with one referring to the opinion that one totally disagrees with a statement to seven indicating that one totally agrees with the statement.

BM Experimentation (BMEX) was measured using scales derived from Sosna et al. (2010). In line with the conceptualization of BMEX as activity, scales were used that measure the resources and efforts taken to engage in this activity. The constructs Operating Model (OM) and Enterprise Architecture (EA) were measured along scales from Ross et al. (2006) and Lindgardt et al. (2009), with the addition of some scales developed by Op 't Land et al. (2009) and Bernus et al. (2003). The dependent variable was measured along two scales to capture overall business performance, which have long been recognized in strategy research (Su, Tsang, & Peng, 2009; Venkatraman & Ramanujam, 1986).

Firm characteristics

Firm characteristics were either measured as dichotomous or converted to binary by manually establishing a threshold for separation. Size groups were classified according to the definition of the European Committee and refer to firms with 0-9, 10-49 and 50-249 employees for the micro, small and medium sized firms respectively. To separate age groups, a threshold was chosen separating the younger, start-up firms from the older, mature firms. It must be noted that binary separation removes most of the detail present in the distribution of firm's age (Figure S1B), and that many approaches exist – most of which are based on various indicators, to classify firms into start-ups and more mature firms. However, it goes beyond the scope of the current research to examine the firm's age in such level of detail. Among those that rely on a binary age segregation, different thresholds have been proposed. For example, Alon et al. (2018) use 11 years to separate start-ups from mature firms. Given the heterogeneity of our population, comprising firms from all different industries, we argue a higher threshold is more suitable to optimize the balance between false negatives and false positives. Hence, we select 16 years as threshold, contrasting the mature firms aged at 16 and older to the younger group aged between 0 and 15.

	Construct, items	Reference
BMEX	*During last year, our enterprise*	
BMEX1	Experimented with the (implementation of) their business model	Sosna et al. (2010)
BMEX2	Had a specific team to manage business model changes	Sosna et al. (2010)
BMEX3	Allocated budgets for business model experimentation	Sosna et al. (2010)
OM	The changes in your business model can have an effect on what your do on a daily basis. To what extent did changes in your business model lead to new ways of. . .	
OM1	Standards how you deliver products/services to customers	Ross et al. (2006)
OM2	Division of work between your enterprise and external partners	Ross et al. (2006)
OM3	Ways to manage cost to deliver products/services profitable	Lindgardt et al. (2009)
OM4	Ways to execute processes	Lindgardt et al. (2009)
OM5	Organizational structures	Lindgardt et al. (2009)
EA	*To what extent did changes in your business model lead to changes in your. . .*	
EA1	Key Business processes	
EA2	Information Technology	Ross et al. (2006)
EA3	Internal controls to monitor processes	Op't Land et al. (2009)
EA4	Business processes standardization	Ross et al. (2006)
EA5	Business processes integration	Ross et al. (2006)
EA6	ICT applications	Ross et al. (2006)
EA7	ICT infrastructure	Ross et al. (2006)
EA8	Social media usage	Bernus et al. (2003)
EA9	Business/organization structure	Bernus et al. (2003)
PERF	*What is the level of agreement with the following statements? [I am satisfied with ...]*	
PERF1	the sales growth of the enterprise	Su et al. (2009)
PERF2	the profit growth of the enterprise	Venkatraman & Ramanujam (1986)

Table 8 Overview of items used for construct operationalization.

4.4 Measurement model

Variable Screening

Within the questions under investigation, no missing rows were observed, i.e. all items were represented by an integer between 1 and 7. From the total of 586 respondents, 2 rows had a standard deviation of zero indicating unengaged responses which we therefore deleted from the sample. The following analyses were performed on the remaining 584 respondents.

Exploratory Factor Analysis

Because the scales originated from different work, discrepancies may occur when measurement models are evaluated. Hence, to evaluate the used scales and to explore the underlying structure, an exploratory factor analysis was performed.

We ran an exploratory factor analysis in SPSS 23 using maximum likelihood method with extraction based on eigenvalues. Rotation was done using Promax method. To test for adequacy, we did a KMO and Barlett's test and found an adequate fit evidenced by the KMO value of 0.880 and the Berlett's Test yielding 0.000 significance. All communalities were above the 0.3 threshold. The 4-factor model explained 61.51% of the total variance, exceeding the commonly accepted cut-off point of 50%. We observed zero per cent nonredundant residuals, below the 5.0% threshold suggested in literature. The factor loading of the items were all above 0.5, which proves evidence for convergent validity. We investigated the Pattern Matrix and did find cross loadings of five items of the Enterprise Architecture factor to the factor of Operating model, namely EA9, EA5, EA4, EA3 and EA1. Because they belonged to a large latent reflective factor (N = 9 items), these items were somewhat redundant, and were therefore removed. More specifically, they represent Enterprise Architecture at a higher level of abstraction, referring to the concept as "organization structure" (EA9), "key business processes" (EA1), and "internal controls to monitor processes" (EA3) which caused an overlap when combined with items for the latent factor Operating Model. After these adjustments, evidence of discriminant validity was observed by the pattern matrix without cross-loadings. Discriminant validity was further evidenced by the Factor Correlation Matrix having all non-diagonal values, i.e. factor correlations, below the 0.7 threshold. Our results showed evidence of reliability, as can be seen from the values of Cronbach's alphas, which exceeded the 0.7 benchmark for all of the constructs (Table 9).

Confirmatory Factor Analysis

We continued with a confirmatory factor analysis to analyse the validity of the measurement model. After the initial run of the CFA in AMOS 23, strong correlations (0.7) were observed between the factors of EA (Enterprise Architecture) and OM (Operating Model), which is understandable due their overlapping role in the implementation process of new Business Models. To accommodate for the high inter-construct correlations, we modelled BM implementation (BMIM) as a second order reflective construct that was loaded with both EA and OM as first order reflective latent factors (Figure 13). We investigated the modification indices (MI) and co-varied two error terms that belong to items of the same latent variable. The CFA for the total sample resulted in a good fit of the measurement model (X2: 82.17, df: 48, CFI: 0.99, SRMR: 0.026, RMSEA: 0.035).

A configural invariance test revealed an adequate goodness of fit when analysing a freely estimated model across the groups of firms differing in firm characteristics (Table 10). We did a metric invariance test by constraining the models to be equal and did a chi-square difference test between the fully constrained and unconstrained models and found them to be invariant for all the moderators (Size $\Delta X2$ P = 0.877, Gender of CEO $\Delta X2$ P = 0.17, Family $\Delta X2$ P = 0.22, Age $\Delta X2$ P = 0.63).

Pattern Matrix	Factor			
Cronbach's α	0,850	0,886	0,784	0,816
EA2		0,722		
EA6		0,884		
EA7		0,883		
OM1	0,756			
OM2	0,601			
OM3	0,787			
OM4	0,790			
OM4	0,634			
PERF2				0,945
PERF2				0,717
BMEX1			0,706	
BMEX2			0,713	
BMEX3			0,782	

Factor	1	2	3	4
1	1,000	0,671	0,578	0,336
2	0,671	1,000	0,498	0,296
3	0,578	0,498	1,000	0,329
4	0,336	0,296	0,329	1,000

Table 9 Pattern and Factor Correlation Matrix.

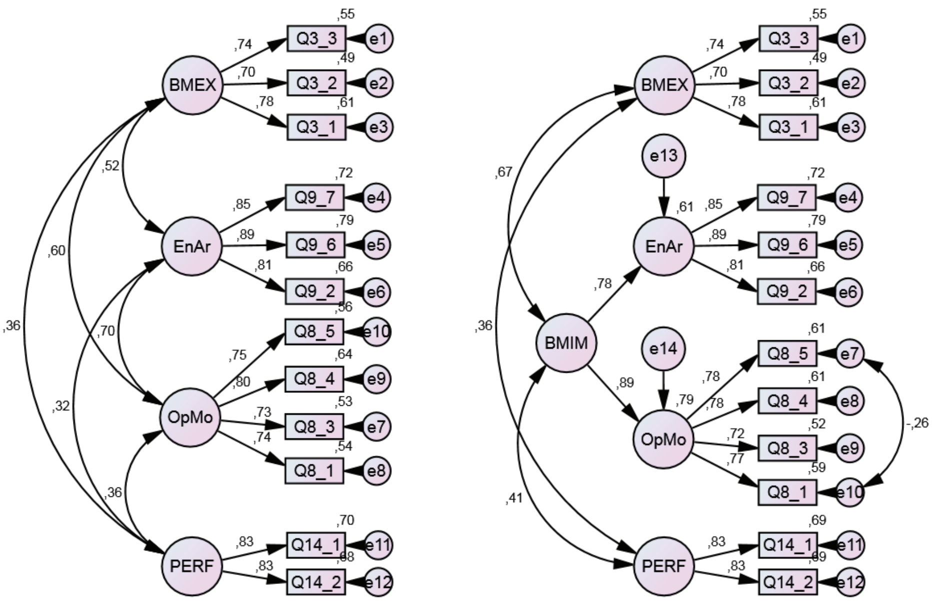


Figure 13 Two CFA models. Initial CFA (left) and CFA with BMIM modelled as second order reflective construct.

	Description	X^2	df	P	NFI	IFI	CFI	RMSEA	sRMR
	CFA Model fit								
1	Initial CFA	99,35	48	0,000	0,97	0,99	0,99	0,043	0,028
2	BMIM 2nd order reflective	99,36	49	0,000	0,97	0,99	0,99	0,042	0,028
3	Optimize MI error terms	82,17	48	0,002	0,98	0,99	0,99	0,035	0,026
4	*Invariances tests*								
	Configural invariance (size, freely)	191,99	144	0,005	0,94	0,99	0,99	0,024	0,036
	Metric invariance (size, constrained)	208,29	168	0,019	0,94	0,99	0,99	0,021	0,050
	Configural invariance (gender of CEO, freely)	138,83	96	0,003	0,96	0,99	0,99	0,028	0,029
	Metric invariance (gender of CEO, constrained)	155,29	108	0,002	0,96	0,99	0,99	0,027	0,030
	Configural invariance (age, freely)	155,61	96	0,000	0,96	0,98	0,98	0,033	0,030
	Metric invariance (age, constrained)	165,43	108	0,000	0,95	0,98	0,98	0,030	0,033
	Configural invariance (family, freely)	139,18	96	0,003	0,96	0,99	0,99	0,028	0,033
	Metric invariance (family, constrained)	154,57	108	0,002	0,96	0,99	0,99	0,027	0.039
5	*Common method bias*								
	With CLF, freely	47,05	35	0,084	0,99	0,996	0,996	0,024	0,019
	With CLF, constrained zero	82,15	47	0,001	0,98	0,99	0,99	0,036	0,026

Table 10 Model fit of CFA optimization.

Composite reliability is a generally accepted measure for reliability (CR > 0.7) and indicates the fraction of true score variances and covariances in the composite of indicator variables related to construct compared to the total variance of the composite. More intuitively, this is used to measure the degree to which measures are from random samples and yield consistent results across situations.

The average variance extracted can be used as a measure for convergent validity and indicates the amount of variance in indicator variables that a construct is managed to explain. The AVE can be computed by dividing the sum of the squared factor loadings by number of items in the model.

Convergent validity was obtained as evidenced by the AVE (>0.5), reliability as indicated by the CR values (>0.7) and maximal reliability values (>0.8), and discriminant validity based on the square root of the AVE being bigger than any of the inter-factor correlations (Table 11)

Next, we did a common method bias test where we compared the unconstrained common latent factor (CLF) model to the fully, zero constrained common method factor model. In the presence of the CLF, the regression weights of the indicators to the CLF did not exceed values above 0.5, which led us to believe that no indicators dominantly permeate in the outcome of the other variables (Figure 14). In other words, no item was present that abnormal shared variance with the other indicators (Figure S3). Despite the absence of abnormalities, in the chi-square difference test, the shared variance came out to be significant (ΔX2: 35,1; Δdf: 12; P: 0,000). To accommodate with this bias, the CLF was retained in the CFA model.

	CR	AVE	MSV	MaxR(H)	PERF	BMEX	BMIM
PERF	0,816	0,689	0,164	0,816	**0,830**		
BMEX	0,785	0,550	0,445	0,891	0,358	**0,742**	
BMIM	0,820	0,696	0,445	0,930	0,405	0,667	**0,834**

Table 11 Validity of constructs. Table listing the Composite reliability (CR), Average variance extracted (AVE), Maximal shared variance (MSV), maximal reliability (MaxR), the inter-construct correlations and the square root of the AVE on bold on the diagonal.

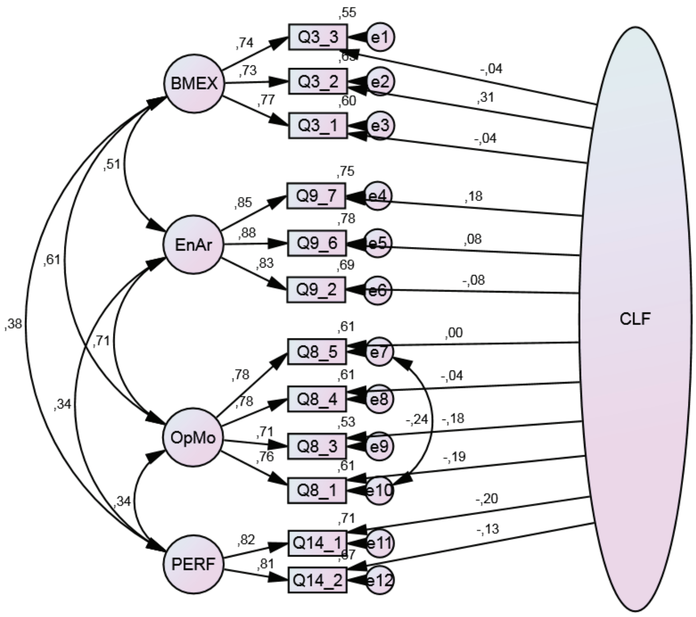


Figure 14 CFA in the presence of the Common Latent Factor (CLF).

The introduction of a second-order reflective latent factor brought a simplification to the conceptual model (Figure 15). In the initial model, the BMIM phase was considered as two separate activities, with one causing the other. During the evaluation of the model, it turned out these activities were highly correlated, and no clear separation could be made. BMIM represents both changes in the OM and EA, and therefore fulfils the role as mediating factor between BMEX and PERF.

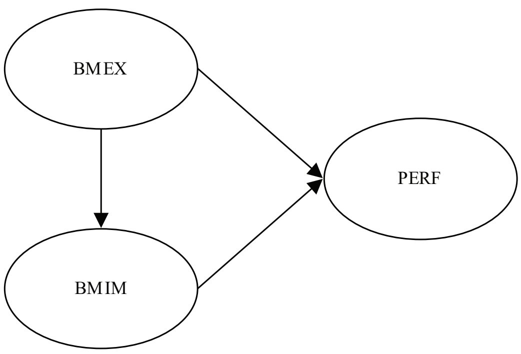


Figure 15 Renewed conceptual model.

Overall, these results indicate an adequate goodness of fit of the measurement model (Table 12). With the exemption of the p-value of the Chi-square test, all fit indices surpassed recommended cut-off values. As pointed out by SEM methodologists, large-N (>400 cases) often fail to obtain a significant Chi-Square value since the test is inflated by sample size (e.g. Jöreskog, 1969). Although the Chi-square test is traditionally considered as substantive tests of fit for SEM, due to its sensitivity to sample size it is often no longer relied upon as a basis for acceptance and rejection. Taken this, we believe the measurement model can be accepted and used as a basis for subsequent analyses.

Fit indices	Value	Recommended	Source
X^2 / (df)	1.72	< 3	Kline, 2011
p-value	0.02	> 0.05	Barrett, 2007
NFI	0.98	> 0.95	Hu & Bentler, 1999
IFI	0.99	> 0.95	Hu & Bentler, 1999
CFI	0.99	> 0.95	Byrne, 2010
RMSEA	0.04	< 0.06	Hu & Bentler, 1999
SRMR	0.03	< 0.09	Hu & Bentler, 1999

Table 12 Overview of model fit.

4.5 Analysis approach: SEM

After validation of the measurement model, factor scores were imputed using linear regression in AMOS. The LCA and fsQCA have a limitation in the number of input variables, and therefore this step is inevitable for these analyses. To preserve the same input for all three analyses, we chose to select the imputed factor scores as basis for all techniques. Thus, all the firms were given numbers representing their activity in the latent variables. Firms reporting low satisfaction or activity in certain items would receive a low score for the variable and firms reporting higher on the Likert scales would receive a higher score for the respective variable. There exists debate on the necessity of factor score imputation for SEM, because the error variance is accounted differently in the composite model. To take this effect into account, the full SEM will be analysed and compared with the imputed model. Before we elaborate on the details of the SEM analysis approach, a brief evaluation will be given on the imputed factor scores.

To identify potential influential records in the imputed data set, we ran linear regressions and investigated Cook's distances for the two latent variables that relate to the dependent performance variables (Figure 16). Although the outliers for BMEX to PERF were the same as those for BMIM to PERF (top in graphs), none of these relations resulted in observations having Cook's Distances greater than 0.1 (max 0.038), indicating the imputed data did not contain abnormal records. Likewise, analysis of the Mahalanobis distance did not reveal severe abnormalities with an average value of 2.0 and a max of 11.3. Collinearity diagnostics revealed variable inflation factors (VIF) of 2.35 and tolerance values above 0.42, surpassing the cut-off values that are suggested in the literature, below 3.0 and above 0.1 respectively. Considering these numbers, no additional respondents were removed, and subsequent analyses were performed on the remaining 584 firms.

After evaluation of factor scores, the approach can be set to perform the SEM analysis. The SEM analysis will be performed using AMOS. The model fit will be evaluated globally, by the model fit parameters NFI, IFI, CFI, RMSEA and sRMR. Then, the relations of the hypotheses will be assessed locally, by the R-square and P-values.

The SEM analysis will involve evaluation of direct effects, mediation effects and moderations effects. Direct effects are the effects of BMEX and BMIM on PERF and analysis thereof will reveal the significance of BMI's performance implications using this conceptualization. The mediation effect of BMIM will be investigated following Bootstrapping method. This analysis will address whether BMIM should be considered as progression of BMEX, and whether it influences the effect of BMEX on PERF. Finally, the moderating effect of the four firm characteristics will be assessed via multi-group comparisons. Here, the extent by which the firm characteristics influence these relations will be revealed. This later analysis can be useful to identify which subgroups are more satisfied with the results of their BMI efforts.

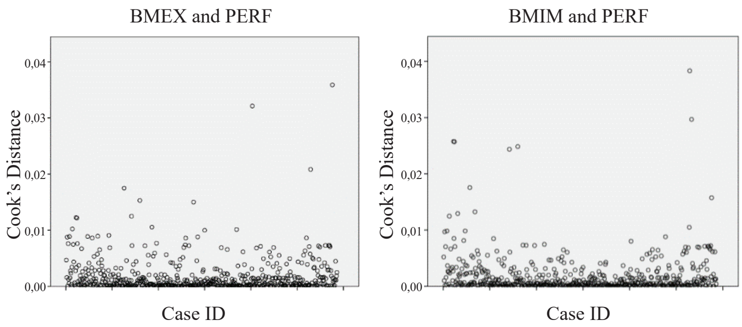


Figure 16 Cook's Distances for BMEX:PERF and BMIM:PERF.

4.6 Analysis approach: LCA

In the LCA, the same constructs will be modelled as in the SEM. BMI engagement here represents the BMI efforts (i.e. BMEX and BMIM) and its consequences (PERF). The LCA will help understand the structure of the data regarding these concepts. By identifying clusters in the data with activity in these concepts, the LCA results may provide valuable insights.

Before the LCA can be performed, an additional manipulation to the factor scores is needed. The imputed data from the CFA will be rounded to the closest integers to obtain ordinal data for the latent variables between 0 and 7 (Figure 17). This data will serve as input for the analysis in LatentGOLD 51. Next, an estimation of the optimal number of latent classes will be done by minimizing the bivariate residuals (BVRs) and the Bayesian information criteria (BIC).

The direct effect of the firm characteristics will be investigated by adding the firm characteristics as covariates to the base model. This approach enables to elucidate the effect of firm characteristics on the cluster profiles. By comparing the effects of these analyses, the firm characteristics can be ranked based on their impact on the model.

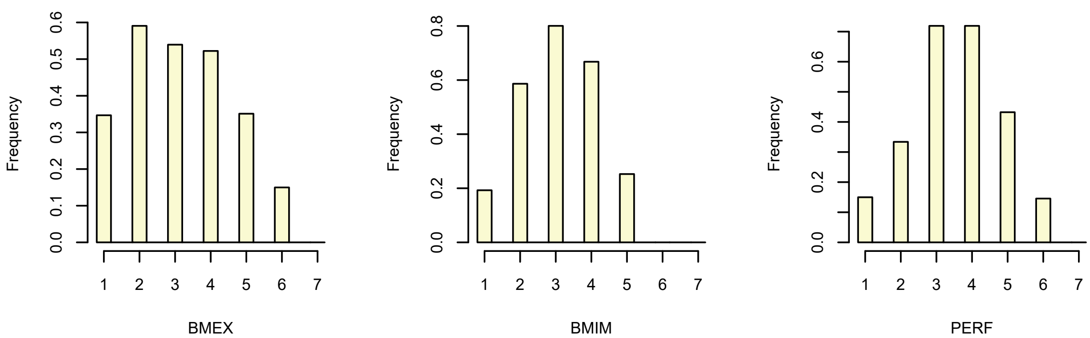


Figure 17 Histograms showing the frequencies of the rounded imputed scores for the latent variables.

4.7 Analysis approach: fsQCA

FsQCA follows a configurational approach that is considerably different from regression-based methods (RBM). In contrast to RBM, which investigate direct effects of the construct and the dependent variable, fsQCA follows an approach were combined information from constructs is used to explore subsets that explain the outcome (Figure 18). FsQCA is especially value when relations are asymmetric. To clarify that our model involves to some extent asymmetric relations, we investigated the factor scores of the constructs.

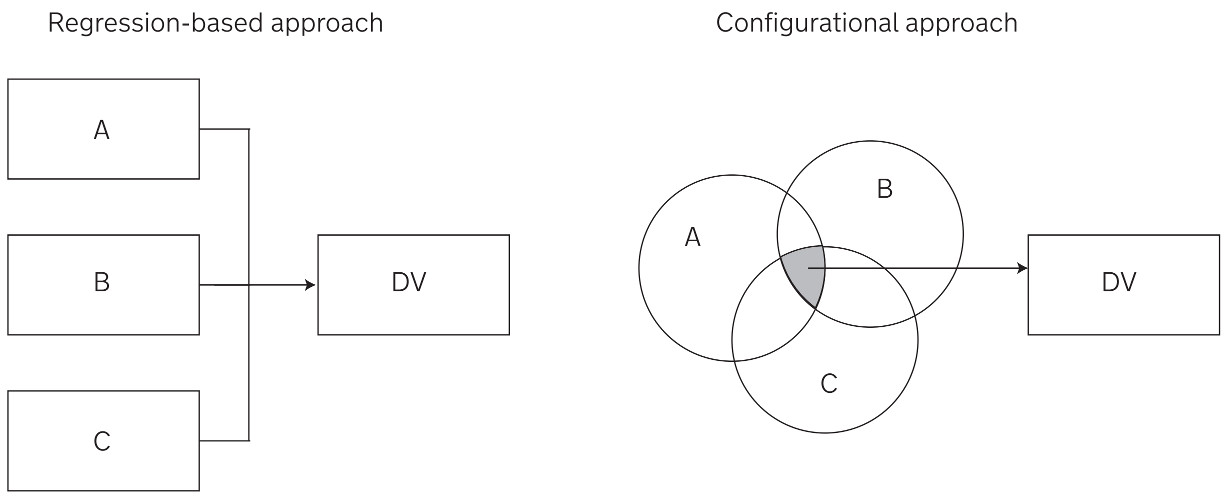


Figure 18. Two approaches to studying relations.

We computed kernel densities of the normalized scores. Kernel density estimation (KDE) is a way to estimate the probability density function of a random variable and can help to smooth the data and find a shape of the relation when the scatter plot is cloudy (Emmenegger, Schraff, & Walter, 2014). Especially, when the sample size is high, the direction of the relation might be less evident from the scatter plot and a KDE can help to detect asymmetric relations or quantify the extent to which a relation is asymmetric (Figure S2, Supplement B).

BMEX and BMIM have an asymmetric relation regarding the dependent variable, which is different from the correlation that they have with respect to each other (Figure 19). For example, while high BMEX appears to correlate with high PERF, high PERF does not necessarily correlated with high BMEX. Likewise, high BMIM has a correlation with high PERF but high PERF not so much with high BMIM. These relations can be understood by considering the complexity of the variable PERF. Given that many factors can influence PERF, a high value for PERF is unlikely to correlate with these practices. These asymmetric effects, suggesting a sufficient but not necessary relation to the dependant variable, are not considered when using regression-based methods including SEM, which assume a causal symmetry (Liu et al., 2017). The fsQCA, therefore, can be a valuable extension of the SEM since it includes this notion.

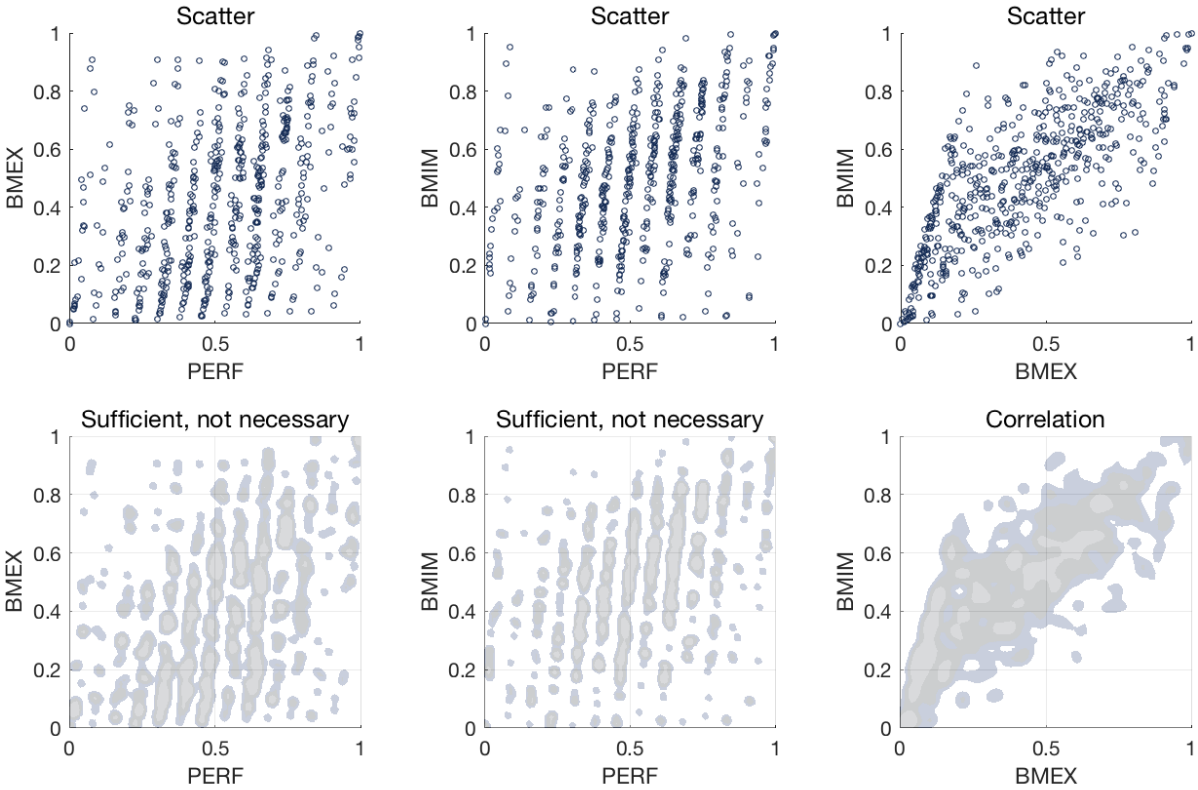


Figure 19 Kernel densities of normalized scores after regression imputation in the presence of a common latent factor.

Similar to the LCA, the fsQCA requires an additional manipulation of the factor scores before analysis can be performed. In the fsQCA this process has been referred to as calibration (Ragin, 1987). There are different ways by which data can be calibrated, and one should consider the advantages and drawbacks of different ways when selecting a calibration method.

In general, there are three different ways by which data can be calibrated (Ragin, 2008). The simplest is the qualitative set approach, which basically allows researchers to manually assign fuzzy set scores to the original variables. The advantage of this approach is that it allows scientists to use the qualitative difference in responses and translate this into non-linear calibration ways. In addition, when combining items to measure latent variables, Boolean operators can be used to assign fuzzy scores. For example, in the case of multiple dichotomous items that build up a latent variable, AND/OR operators can be used to rank configurations of responses and assign fuzzy scores according to theoretical knowledge of the variable of interest. Although this method might be the most flexible, it comes with the risk of subjective assumptions that researchers might not degree upon.

Direct calibration is an automated approach and that is based on the establishment of three anchor points in the data, which are used to normalize the data in the interval according to a certain function. To demonstrate how this can be done, we adjusted the code provided by Liu et al. to perform an automated piecewise linear calibration (Supplement C). Other forms of direct calibration include logistic distribution, such as S-shaped functions or bell-shaped functions (Figure 20). The advantage of using non-linear ways of calibration is that this can help to contrast the data, i.e. make points a little below average lower and points a little above average higher and obtain a measurement instrument that is more sensitive to small perturbations from the average neutral response on Likert scales.

Lastly, calibration can be done using the indirect method, an approach that consist of two consecutive phases. Before calibrated values are assigned to the data points, the data is sorted and cut into equal intervals based on a given threshold, e.g. quintile cuts. Then, a binomial logistic regression with a fractional polynomial equation is applied to map the data in the intervals. This second step, however, is rarely used in practice, and often scholars start the analysis sorting, cutting the data, and then manually assigning fuzzy scores to the different plateaus (Hsiao et al., 2015).

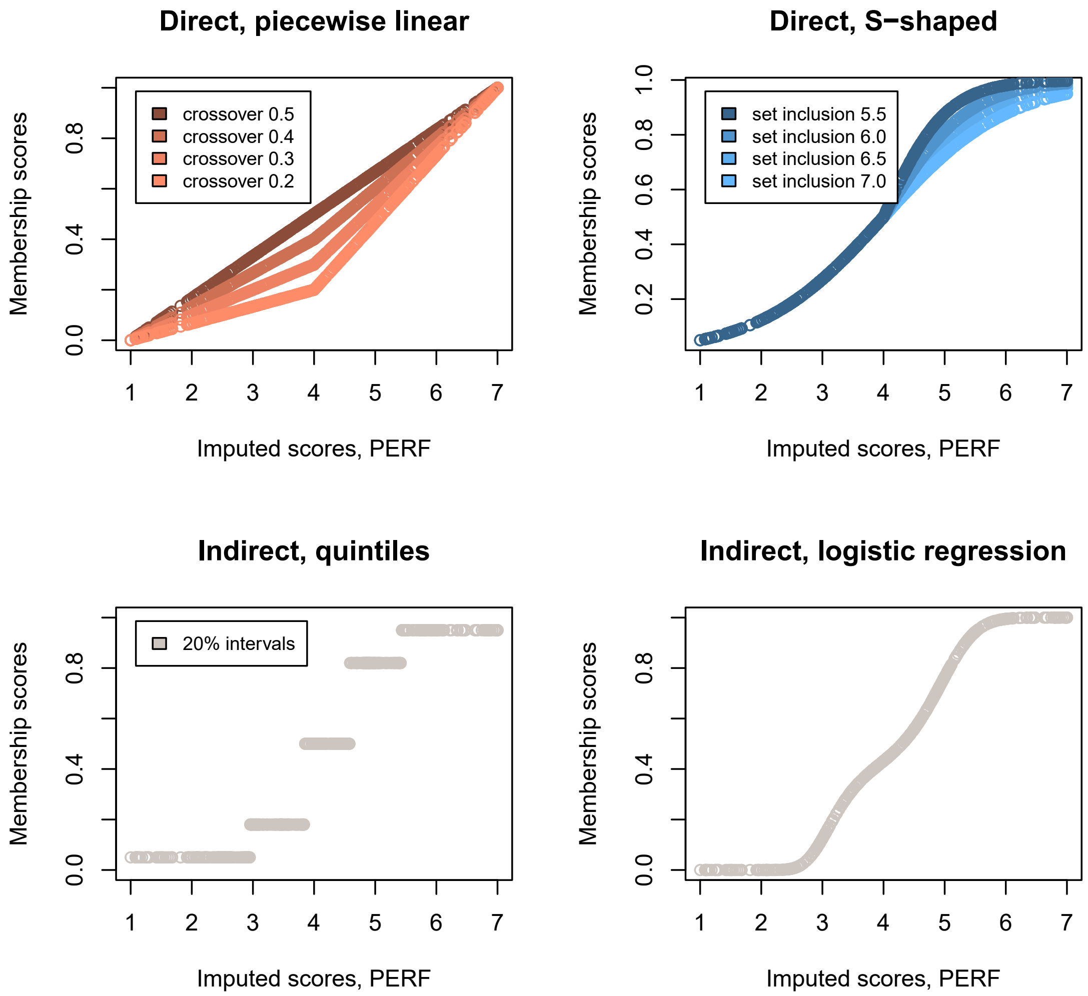


Figure 20 Different ways of fsQCA calibration. Piecewise linear calibration (left) or S-shaped distributions (right). Indirect calibration consists of two steps: sorting and cutting of the data (left) and logistic regression to map the data in the intervals.

In this study, direct calibration will be followed based on a S-shaped function. This is particularly valuable in the case of 5/7-Likert scales, as is used in this research. Following this method can help to suppress the effect of neutral responses (Likert response 4) while it will enhance the effect of response deviating from this value.

After calibration, the fsQCA analysis will be performed by adding the latent variables together with the firm characteristics. This analysis will be deepened by doing multi group comparisons and running the analysis for both high and low PERF. This can provide insights on how configurations explain the outcome (PERF) and what firm characteristics play crucial roles. The major advantage of the fsQCA analysis is that is enables identification of configurations. Insights from this analysis can be of special interest for policy makers that aim at targeting weaker subpopulations.

The analysis will end with a comprehensive evaluation of the robustness of results. In general for large-N data, QCA methodologists have expressed their concerns about the lack of robustness test to enhance confidence in the proposed relationships (Emmenegger et al., 2014). We aim to strengthen our findings by applying different robustness tests. Solutions are compared depending on different frequency and consistency thresholds. This will help to validate whether results are consistent for different parameters. Robustness of findings is further investigated based on a Monte Carlo-like approach described by Emmenegger et al. (2014), in which the identification of prime implicants is compared within iterations of randomly simulated subsamples. This test will help to evaluate the dominance of small parts of the data. Together, these tests contribute to the reliability and external validity of the findings.

4.8 Comparing Methods

Now that we outlined the basic approach for the three methods, we elaborate on some of the method-specific characteristics to contrast the differences. By doing so, we aim to show that a combined use can help to overcome method-specific drawbacks and can provide a comprehensive perspective on the data (Table 13).

In general, the basic approach of these methods is different. While SEM is commonly used as confirmatory approach to test hypotheses, LCA is often applied to obtain a descriptive view on the data and fsQCA is a powerful tool to explore configurations among many.

The imputed factor scores form the starting point for the techniques, yet there are some notable differences in whether additional manipulations are required and on the statistical approach of each method. As mentioned, for the SEM analysis itself, imputing factor scores is no necessity, although it is used, especially when models have severe complexity. No additional manipulations are needed to perform SEM on the scores after imputation. A latent class cluster model assumes that the latent variable is categorical, and therefore factor scores will need to be rounded before they can be used as input. The fsQCA requires calibration to recode all the observed variables within a range of zero to one. Calibration is an essential process of QCA that should be based on theoretic logic since it can have a strong impact on research design and results.

Within the research objectives of this thesis, different aspects can be pointed out that can be investigated by a unique analysis feature of each method. The SEM technique enables construction of a model in which mediation effects can be studied and validated. This makes it possible to clarify the potential mediation effect of BMIM. The LCA provides an overview of cluster profiles that help understand the underlying structure of the data. Especially, since the sample size is large and representing the European SME economy, this feature may provide insights that can be applied to the current economy. Finally, the fsQCA enables quick identification of well-performing and poor-performing subpopulations by zooming in to groups of firms with different characteristics. This analysis may be useful to rank configurations and provide policy makers fruitful overviews.

Considering the conceptual models discussed in Chapter 3, differences can be pointed out in the terminology and role of the constructs in the techniques. While all techniques will use the same constructs as basis for analysis, the role of the constructs may differ between techniques. For example, PERF is the dependent variable in the SEM and the outcome in fsQCA, but an indicator in the LCA, because the LCA has no distinguish between its input indicators. BMEX and BMIM will be endogenous variables in the SEM, an indicator in the LCA and conditions in the fsQCA. The real difference is in the way firm characteristics are instigated in the three methods. In the SEM, these will be studies as moderators by performing multi-group comparisons. In contrast, the LCA and fsQCA will investigate a direct role of firm characteristics on the other constructs. In the LCA, this will be studies by adding the characteristics as covariates to the model, while the fsQCA will do so by comparing configurations in the presence and absence of the outcome PERF.

	SEM	**LCA**	**fsQCA**
Main Approach	Confirmatory	Descriptive	Exploratory
Manipulation to factor scores	None	Round	Normalize and Calibrate
Unique analysis feature	Mediation effect	Cluster profiles	Configurations
Explained variance[1]	R-squared	(pseudo)R-squared	Coverage
Conceptual Model			
Role of PERF	Dependent variable	Indicator	Outcome
Role of BMEX, BMIM	Endogenous variable	Indicator	Condition
Role of firm characteristics (evaluation approach)	Moderator (multi-group)	Direct (covariate)	Direct (condition, multi-group)

Table 13. Comparing three techniques for multi-variate analyses.

4.9 Conclusion

This Chapter introduced the dataset under investigation and elaborated on how it was collected during the ENVISION project. Based on the conceptual models presented in Chapter 3, an operationalisation was proposed to construct a measurement model. Validation of the measurement model was done in EFA and CFA and came with some adjustments that resulted in the final model as presented in Section 4.4.

In the second part of the Chapter, the analysis approaches were discussed for the different techniques: SEM, LCA and fsQCA. While the same measurement model is applied for all methods, differences exist in how these methods work. The Chapter finished by contrasting some of these differences.

Aligning analyses between these techniques is not an easy task, and it certainly not always possible. However, whenever these techniques can be aligned, they constitute to a powerful tool enabling a comprehensive analysis of the data. In the next Chapter, these techniques will be applied to evaluate the models and hypotheses.

[1] A discussion on the computation of the explained variance is provided in the Appendix (Supplement D)

Chapter 5 Results

This Chapter will begin with an overview of some descriptive characteristics of the data. The analysis will be continued by explanatory models. The SEM will be analysed to test the hypotheses presented in Chapter 3. Next, LCA will be performed to overview clusters and investigate their profiles. Then the fsQCA results will be presented and different configurations will be discussed. In the end of the Chapter, results will be compared, and the applicability of findings will be discussed.

5.1 Descriptive Analysis

As discussed in Chapter 4, 37% of the firms that participated in this study, made changes in their business model within the last two years. From this group, 38% uses the label of Business Model Innovation. The remaining majority did make changes in their business logic but did not use this terminology. An often-acknowledged definition of BMI originates from Teece, and conceptualizes the constructs along three dimensions, value proposition, value capture and value creation. Here, these dimensions are measured by multiple items. Most of the items that concern changes in BMs, were answered above neutral for most respondents (Figure 21).

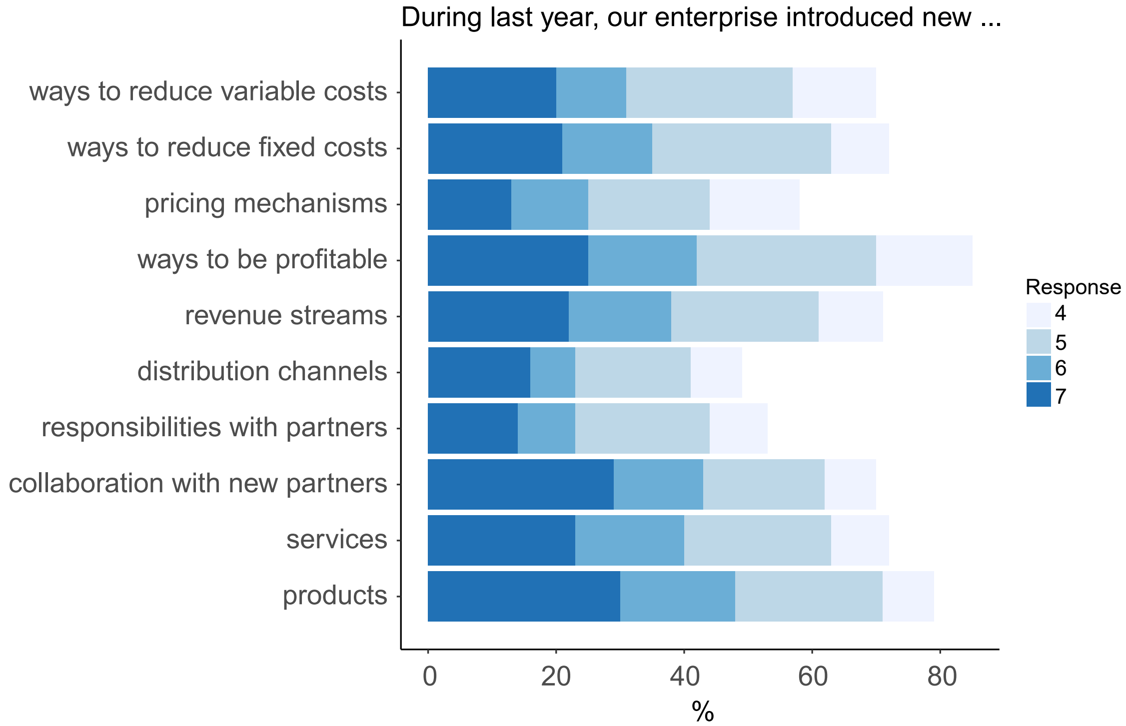


Figure 21 Responses to examples of BMI

During the validation of the measurement model, a selection was made in questions that are used for measurement. From the mosaic plot, it becomes clear that most of the selected items were answered heterogeneously although there are some exceptions (Figure 22). The perceived performance questions (PERF1, PERF2) had few respondents answering close to the lower bound of the Likert scale and its peak was located at a response value of five, indicating that managers in general were quite optimistic about the business performance. The items regarding BM experimentation had a strong peak at the lower boundary of the scale, which suggests that quite a few firms did not engage in BM experimentation at all or at least, in the way measured by these scales.

The present study focuses on perceived performance indicators rather than on actual ratios. It is important to consider implications for this choice. When comparing estimated growth percentages to perceived indicators, clear differences can be denoted (Figure 22). Foremost, the shape of the estimated growth histogram is more like a Poisson distribution while the perceived indicators lie along a normal distribution. In contrast to the estimated values, which can take any integer value between possible ranges of growth differences, perceived values are limited to the only seven categorical values on the Likert scale.

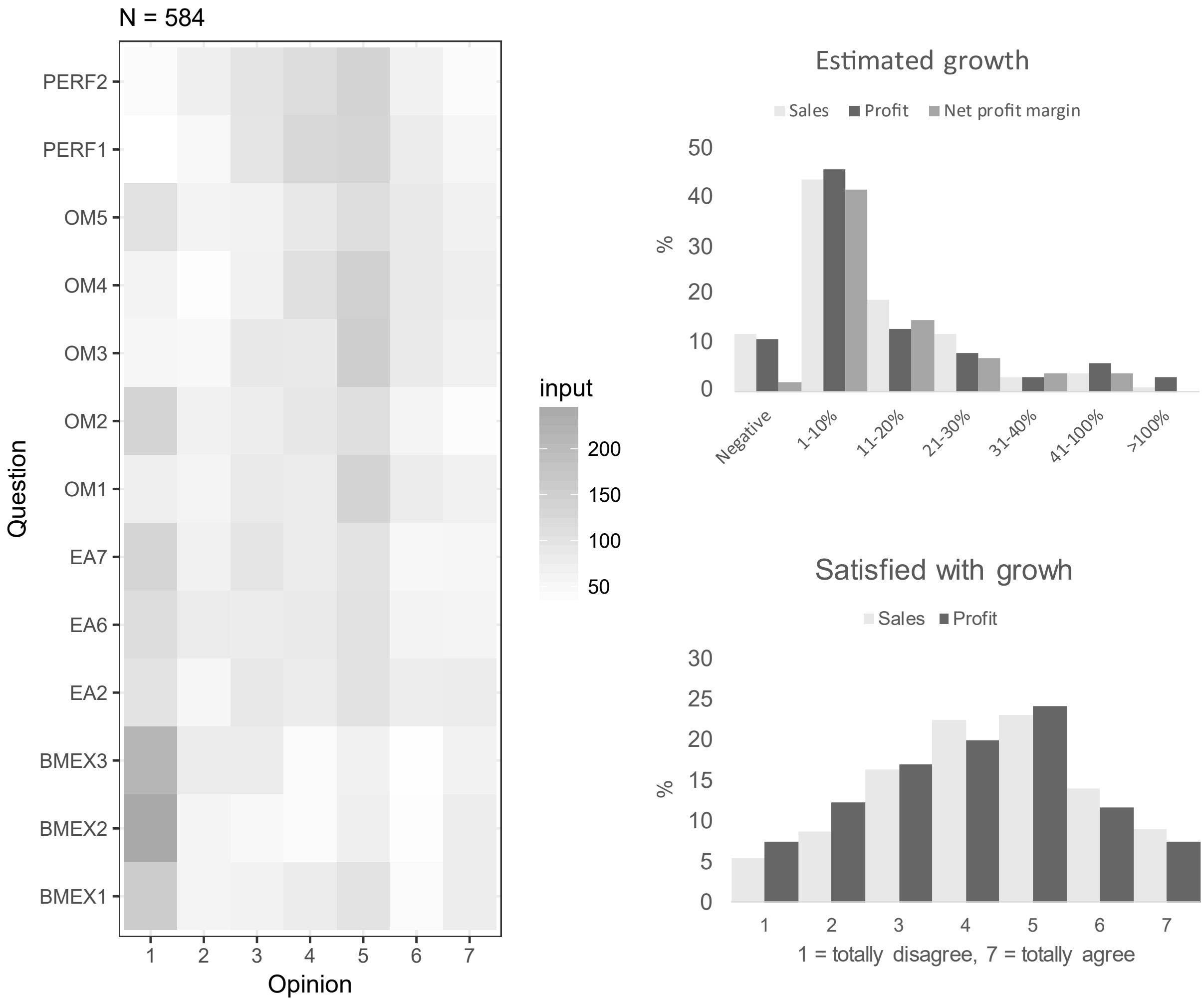


Figure 22 Responses to questions in the measurement model. Top: mosaic plot of items in measurement model. Bottom: Histograms presenting the items for estimated growth performance and perceived growth performance.

5.2 SEM

Model

For the SEM analysis, both the full SEM as the imputed model were computed (Figure 23). The full SEM accounts for measurement errors and is therefore stricter in its results. Therefore, the hypotheses testing below will rely on results from the full SEM. It most be noted, however, that subsequent analyses in the LCA and fsQCA will rely on the imputed factor scores, as visualized in the imputed model.

The structural model of the overall sample (N = 584) was fitted in AMOS 23. The model explained 44% and 18% of the variance as indicated by the squared multiple correlations of BMIM and PERF respectively (Figure 23).

Direct effects were investigated by their regression weights and significance levels. Evidence was found that BMEX has a positive effect on PERF (full SEM: beta = 0.16, P = 0.043). Likewise, BMIM was found to have a strong effect on PERF (full SEM: beta = 0.30, P < 0.001).

The mediation effect of BMIM was tested by an Estimand in AMOS following Bootstrapping method. The indirect effect measured in a bias corrected 90% confidence interval was 0.17 and appeared to be significant (P = 0.001). Together, these results are consistent with the hypotheses except for H1 (Table 14). H1 was not measured in the SEM since OM and EA were found to correlate during the CFA, which is why BMIM was modelled as second order construct.

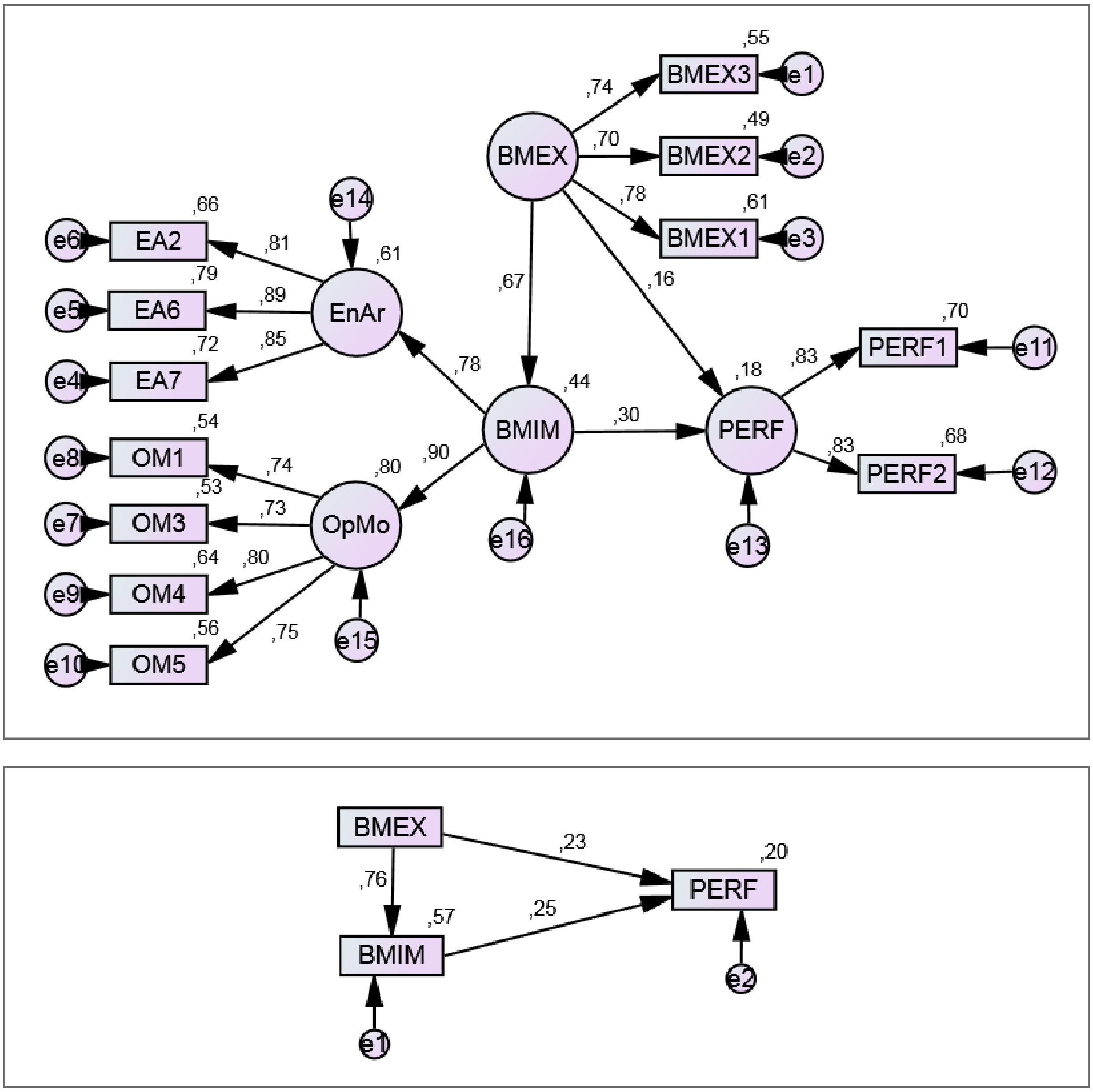


Figure 23 Analysis of the full SEM (top) and imputed model (bottom).

	Type	Hypothesis	Evidence	Conclusion
H1	Direct	OM changes → EA changes	-	Not measured
H2	Direct	BMEX → PERF	$\beta = 0.16$, P = 0.043	Supported
$H3_{a,b}$	Direct	BMEX → BMIM	$\beta = 0.67$, P < 0.001	Supported
$H4_{a,b}$	Direct	BMIM → PERF	$\beta = 0.30$, P < 0.001	Supported
$H5_{a,b}$	Mediation	BMEX → BMIM → PERF	$\beta = 0.17$, P = 0.001	Supported

Table 14 List of hypotheses with associated evidence and conclusion.

Multi-group analysis

For the multi-group comparisons, we did a chi-square difference test where we freely estimated the two models except constraining the main paths (BMEX -> PERF, BMEX -> BMIM, BMIM -> PERF). Although none of the moderators were found to show significant differences in this test, some moderating effects were observed during the group comparisons (Table 15).

For the size groups, we observed lower explained variance in the group of small firms compared to the micro and medium sized firms (13% small, versus 16% for micro and medium). This reduced explained variance resulted from little differences between the relations to PERF. Between the group of female CEOs versus male CEOs, we did observe considerable difference in the R-squared (18% male, 26% female), together with a increase in the effect of BMEX on PERF and BMIM on PERF. Contrasting the group of family enterprises with non-family enterprises did not reveal changes in explained variance of PERF. Between the age groups, a small increase was observed in the R-squared for young, start-up firms, compared to the older, mature firms (21% young, 16% old). Surprisingly, the effect of BMEX on BMIM was stronger for older firms (β = 0.68 old vs. β = 0.61 young) while the effect of BMIM on PERF was stronger for younger firms (β = 0.30 old vs. β = 0.36 young).

In short, we did observe some differences caused by the moderating effect of the firm characteristics. However, a chi-square difference test did not indicate these changes as significant.

				Standardized regression weights		
Firm characteristic	P-value $\Delta\chi^2$		R^2 PERF	β BMEX → PERF	β BMEX → BMIM	β BMIM → PERF
Size	0.259	Micro	0.19	0.16*	0.65***	0.31***
		Small	0.14	0.13*	0.65***	0.27***
		Medium	0.19	0.16*	0.65***	0.31***
Gender of CEO	0.269	Male	0.18	0.15*	0.67***	0.30***
		Female	0.26	0.19*	0.70***	0.36***
Family vs. Non-family	0.721	Family	0.18	0.15*	0.63***	0.31***
		Non-family	0.18	0.16*	0.71***	0.29***
Age	0.617	Young	0.21	0.14*	0.61***	0.36***
		Old	0.16	0.13*	0.68***	0.30***
P < 0.1*, 0.01**, 0.001***						

Table 15. SEM Multi-group comparisons for the four moderators.

Post hoc power analysis

We did a post hoc power analysis and we did have power to detect significant effects that might have existed therefore we are confident that non-significant effects that we observed were truly not significant. Both for PERF as BMIM the statistical power was above 0.99 based on the R2, number of predictors, sample size and probability level (0.001).

5.3 LCA

Model

We began by estimating clusters from the indicators BMEX, BMIM and PERF, based on their rounded imputed factor scores. Minimizing the Bayesian information criteria (BIC) which takes parsimony into account, suggested that the four-class model is the preferred outcome when performing a traditional latent class fit (Table 16). The four-class model (H3C) had bivariate residuals below 0.3 and explained 24% of the variance of the PERF variable.

Model	BIC_{LL}	L^2	*df*	*p-Value*	*Red.* L^2
H_0	-286.78	764.25	165	7.60E-78	0%
H_{1C}	-637.64	387.91	161	9.20E-21	49%
H_{2C}	-786.77	213.31	157	1.90E-03	72%
H_{3C}	-805.37	169.22	153	0.18	78%
H_{4C}	-787.57	162.54	149	0.23	79%

Indicators	*BMEX*	*BMIM*	*PERF*	*Clusters*	R^2
BMEX	-			0.85	0.72
BMIM	0.202	-		0.84	0.70
PERF	0.001	0.021	-	0.49	0.24

	Cluster1	*Cluster2*	*Cluster3*	*Cluster4*
Cluster Size	0.45	0.31	0.18	0.07
1	0.00	0.00	0.78	0.00
2	0.43	0.02	0.22	0.00
3	0.39	0.14	0.00	0.01
4	0.16	0.42	0.00	0.10
5	0.02	0.34	0.00	0.40
6	0.00	0.08	0.00	0.49
BMEX Mean	2.76	4.33	1.22	5.37
1	0.06	0.02	0.16	0.00
2	0.15	0.07	0.25	0.00
3	0.34	0.24	0.34	0.03
4	0.30	0.36	0.19	0.15
5	0.13	0.25	0.05	0.41
6	0.02	0.07	0.01	0.41
PERF Mean	3.34	3.96	2.73	5.21
1	0.01	0.00	0.42	0.00
2	0.31	0.01	0.55	0.00
3	0.56	0.21	0.03	0.00
4	0.12	0.66	0.00	0.09
5	0.00	0.12	0.00	0.91
BMIM Mean	2.80	4.00	1.61	4.91

Table 16 LCA cluster profiles of the model with four latent classes.

The four-class model consisted of two major Classes 1 and 2 that together represented about three third of the total sample size and were positioned around the mean in terms of their performance and BM activity, with Class 1 performing slightly above average and Class 2 slightly below. The two remaining Classes 3 and 4, were much smaller (17 and 7% respectively) and confirmed the relation suggested by the two dominant classes in a more extreme way. Class 3 consisted of firms that performed below average, had poor BMIM activity and even less or about negligible BMEX activity. On the contrary, Class 4 represented members that performed far above average that simultaneously were actively working on both BMEX and BMIM

Surprisingly, the average values for BMEX and BMIM appeared near linear when ordering Classes based on their performance (Figure S4). This confirms the positive effect of these constructs on PERF, which was tested during the SEM. Because of this linear behaviour, no distinguish can be made between Class behaviour other than the extent to which BMI practices (BMEX, BMIM) are pursued. We will therefore refer to these Classes as poor group (Class 3), fair group (Class 1), good group (Class 2) and excellent group (Class 4).

Covariates

We added covariates to investigate the direct effect of the four firm characteristics on BMI engagement. Table 17 overviews the effect of covariates on the probability of being in the respective classes. First, we added one by one the following covariates to the model with four latent classes: young versus old firms; family versus non-family enterprises; companies with female CEOs versus companies with male CEOs; micro, small and medium sized organizations.

Compared to the older firms, the younger firms had a higher representation in the excellent group and the poor group, while they had lower representation in the good group.

The non-family enterprise group outperformed the family enterprise group regarding their representation in the good group, while family firms had more representation in the excellent group. In the fair group, family firms had higher representation compared to non-family firms.

The firms managed by male CEOs had lower representation in the poor group compared to the firms manged by female CEOs. The representation in the excellent group was near equal. Interestingly, the representation in the fair group was near equal for both groups, making the difference appear in the poor group.

The size of the firm appeared to correlate with representation in the good group and change that was caused by a reduction in the poor group. Thus, micro firms had more representation in the poor group and lower representation in the good group compared to smaller and medium sized firms. However, when focusing on the excellent group, the increase in size appeared to result in an U-shaped pattern.

		Cluster 3	Cluster 1	Cluster 2	Cluster 4
		Poor	Fair	Good	Excellent
	Total (N=584)	0.17	0.45	0.31	0.07
Firm age	Old	0.16	0.45	0.33	0.06
	Young	0.2	0.46	0.26	0.09
Family enterprise	Family	0.17	0.48	0.23	0.12
	Non-family	0.17	0.35	0.4	0.08
Gender of CEO	Female	0.28	0.42	0.24	0.07
	Male	0.15	0.44	0.33	0.07
Firm size	Micro	0.3	0.41	0.22	0.07
	Small	0.16	0.48	0.31	0.06
	Medium	0.07	0.42	0.42	0.09
	SD	0.06	0.04	0.07	0.02

Table 17 Effect of covariates on cluster membership probabilities

Interestingly, the differences in probability means are dominantly caused by differences in the good group and the poor group. This suggests that most group dependent differences are absent in the fair group, and directly interchange between more extreme poor and good group.

With the aim to align LCA results to those of the fsQCA, we continued by studying the addition of multiple covariates simultaneously, thereby mimicking configuration results of the fsQCA (Supplement E). Performing this analysis revealed a dominant effect of the characteristic firm size. This suggests that, among the firm characteristics under investigation, firm size is the most important regarding direct effects on BMI engagement.

5.4 fsQCA

We performed a fuzzy set qualitative comparative analysis to compare different configurations of firms' characteristics leading to an enhanced performance and to account for asymmetric relations. The qualitative comparative analysis was performed in R, using Package QCA v3.2, that implements the comparative method as first described by Ragin and follows an exact derivation of the Quine-McCluskey minimization algorithms (Dusa et al., 2018).

BMEX and BMIM were modelled as conditions with the addition of the conditions size, gender of CEO, age and classification of family enterprises. PERF was selected as outcome variable. Traditionally, it has been argued to be cautious with adding too much conditions for a fsQCA since it could easily produce artefacts or inflate coverage that could result in false interpretations. To account for this, we start with analyses of five conditions, two latent variables (BMEX and BMIM) and three firm characteristics (size, CEO gender, family) and after optimisation and validation we added the last covariate, age.

Calibration

Following the approach of direct calibration, the imputed factor scores were calibrated along a S-shaped logistic function by establishing three anchor points for the latent variables. An artefact of using imputed scores as input is that they could include scores below the minimal value of the categorical scale. To accommodate for this deviation, minimal scores for each construct were equalized to one by adding these differences as a constant to the set. Next, S-shaped curves were fitted that started at one, had turning points at four, and maxima similar to the maximal corrected score of the respective latent variable (Figure S5). We believe it is justifiable to adjust the maximum for fuzzy set inclusion given the varying number of indicators that we used to measure the latent variables. BMIM was measured as a second order reflective variable that was loaded by eight indicators that measure different aspects of BM changes. Intuitively, such a score would result in a more compressed factor score range in comparison to BMEX, that was measured by three indicators, or PERF that was computed out of two indicators. Adjusting these maxima prevents suppression of fuzzy set inclusion, and thus could help to minimize the false negatives. It is important to realize the impact of these adjustments as demonstrated by altering the value for inclusion (Figure S5). In this case, the distribution of [BMEX] and [BMIM] become more aligned for the higher membership scores.

The firm characteristics family enterprise [FET] and gender of CEO [CEOMale] were added as crisp conditions, being either zero or one depending on the presence of the attribute. Firm size [SIZE] was initially calibrated as 0.95 for medium sized firms, 0.7 for small firms and 0.2 for micro firms.

Analysis

The complete truth table lists causal conditions with frequency and sufficiency scores (Table 18). To minimize the truth table and find solutions for the model, cut-off points for frequency and inclusion should be depicted. There is still debate on what values deliver satisfactory validity, and scholars might follow different guidelines dependent on the sample size and other contextual factors. As a start, an inclusion cut-off of 0.75 as initially proposed by (Ragin, 1987) is used to obtain an understanding of the data. Inclusion threshold is set at N = 5, in accordance with studies concerning similar sample size.

Row	[BMEX]	[BMIM]	[CEOMale]	[FET]	[SIZE]	[PERF]	n	incl
1	0	0	0	0	0	1	15	0.61
2	0	0	0	0	1	1	21	0.71
3	0	0	0	1	0	1	11	0.69
4	0	0	0	1	1	1	13	0.7
5	0	0	1	0	0	1	69	0.71
6	0	0	1	0	1	1	99	0.77
7	0	0	1	1	0	1	47	0.75
8	0	0	1	1	1	1	72	0.73
9	0	1	0	0	0	1	1	0.94
10	0	1	0	0	1	1	1	0.94
12	0	1	0	1	1	1	3	0.93
13	0	1	1	0	0	1	9	0.93
14	0	1	1	0	1	1	11	0.92
15	0	1	1	1	0	1	5	0.93
16	0	1	1	1	1	1	10	0.92
17	1	0	0	0	0	1	1	0.93
18	1	0	0	0	1	1	5	0.88
19	1	0	0	1	0	1	1	1
20	1	0	0	1	1	1	3	0.96
21	1	0	1	0	0	1	3	0.93
22	1	0	1	0	1	1	26	0.94
23	1	0	1	1	0	1	7	0.95
24	1	0	1	1	1	1	20	0.89
25	1	1	0	0	0	1	2	0.94
26	1	1	0	0	1	1	8	0.95
27	1	1	0	1	0	1	1	0.99
28	1	1	0	1	1	1	6	0.95
29	1	1	1	0	0	1	19	0.93
30	1	1	1	0	1	1	29	0.93
31	1	1	1	1	0	1	10	0.95
32	1	1	1	1	1	1	35	0.9

Table 18 Truth table showing consistency and frequency of the causal combinations.

A truth table minimization with these thresholds resulted in a solution with diverse causal combinations (Table 19). We focused on the intermediate solution, as it is the most frequently used solution type. While [BMEX] and [BMIM] appear frequently in the solution table, also solutions without these constructs are found to obey to the criteria (e.g. the configuration CEOMALE*fet*SIZE, which refer to small or medium firms with male CEOs in non-family firms, is found as causal condition that explains the outcome). Although causal combinations without the latent constructs appear in the solution with a relative high coverage, they appear to be at the lower limit of the consistency range. When the limits are increased to an inclusion cut-off of 0.85 and frequency cut-off of N = 10, these solutions disappear and [BMEX] and

[BMIM] become dominant conditions to explain [PERF]. Similarly, when the truth table is minimized by row dominance (incl = 0.85, Ncut = 5), both [BMEX] and [BMIM] appear as dominant prime implicants (Figure 24). Hence, the data are largely consistent with the argument that [BMEX] and [BMIM] are a subset of [PERF] and their coverages is 64% and 61% respectively. That is, both variables account for roughly sixty percent of the sum of the membership in [PERF]. Increasing the thresholds to values far above common accepted cut-off points (incl = 0.90, Ncut = 20) yields the solution:

```
BMEX*BMIM*CEOMALE*fet + BMEX*CEOMALE*fet*SIZE => PERF
```

This solution has a coverage of 27 percent and represents the configurations of firms that are engaged in [BMEX], or [BMEX] and [BMIM], and have [CEOMALE], are small or medium in [SIZE] and do not label themselves as [FET].

				Coverage	
			Consistency	**Raw**	**Unique**
Frequency cut = 5, Consistency cut = 0.75					
1	PI	BMIM*CEOMALE	0.87	0.54	0.082
2	PI	BMEX*BMIM*SIZE	0.92	0.45	0.03
3	PI	BMEX*fet*SIZE	0.9	0.27	0.003
4	PI	CEOMALE*fet*SIZE	0.71	0.36	0.092
5	PI	CEOMALE*FET*size	0.71	0.19	0.044
		Solution	0.73	0.81	
Frequency cut = 10, Consistency cut = 0.85					
1	PI	BMEX*BMIM*CEOMALE	0.91	0.45	0.074
2	PI	BMEX*CEOMALE*SIZE	0.88	0.42	0.044
3	PI	BMIM*CEOMALE*SIZE	0.89	0.44	0.062
		Solution	0.86	0.56	
Frequency cut = 10, Consistency cut = 0.90					
1	PI	bmex*BMIM*CEOMALE*SIZE	0.92	0.33	0.099
2	PI	BMEX*BMIM*CEOMALE*size	0.94	0.28	0.075
3	PI	BMEX*CEOMALE*fet*SIZE	0.9	0.23	0.069
		Solution	0.9	0.49	
Frequency cut = 15, Consistency cut = 0.90					
1	PI	BMEX*BMIM*CEOMALE*fet	0.92	0.25	0.045
2	PI	BMEX*CEOMALE*fet*SIZE	0.9	0.23	0.026
		Solution	0.89	0.27	

Table 19 Fs-QCA solutions for different frequency and consistency thresholds.

Robustness

Using fsQCA for large-N data removes one key feature of QCA, its case orientation. In large-N data, it is often impossible to evaluate data at single case level which could make causal inference questionable. QCA methodologists have stressed the importance of robustness tests to enhance confidence of the results (e.g. Emmenegger et al., 2014). Conventional tests mainly focus on changing the criteria for inclusion, as showed in Table 19. Another robustness test that has been proposed comes from a different angle. As demonstrated by Emmenegger et al. (2014), a Monte Carlo-like approach could be used to investigate the effect of dropping cases from the sample. Following this approach, 999 QCA solutions were obtained by randomly deleting 10% before the truth table was minimized following incl = 0.85, Ncut = 10 (Supplement F). Evidence of robustness follows from the similarity of the most frequent prime implicants compared to the found solution earlier (Table 19). From the histogram it becomes clear that BMEX*BMIM*male*fet, not identified in the solution table, appears at higher frequency than BMEX*BMIM*fet, a solution that was found in the solution table (Figure 24). Compared to the original solution, a few new prime implicants were found but they appear very rarely which supports the evidence of robustness.

The baseline solution (incl = 0.85, Ncut = 10) can be visualized by a Venn diagram in which the intersection areas of the causal combinations highlight the group of firms that are in the fuzzy set of [PERF] (Figure 24). [BMEX] and [SIZE] appear in all the solutions, thus fulfil a dominant role among the conditions. This solution provides robust findings and has consistency of 0.89. The coverage of this solution is 0.53, indicating how much of the outcome [PERF] is covered by the solution.

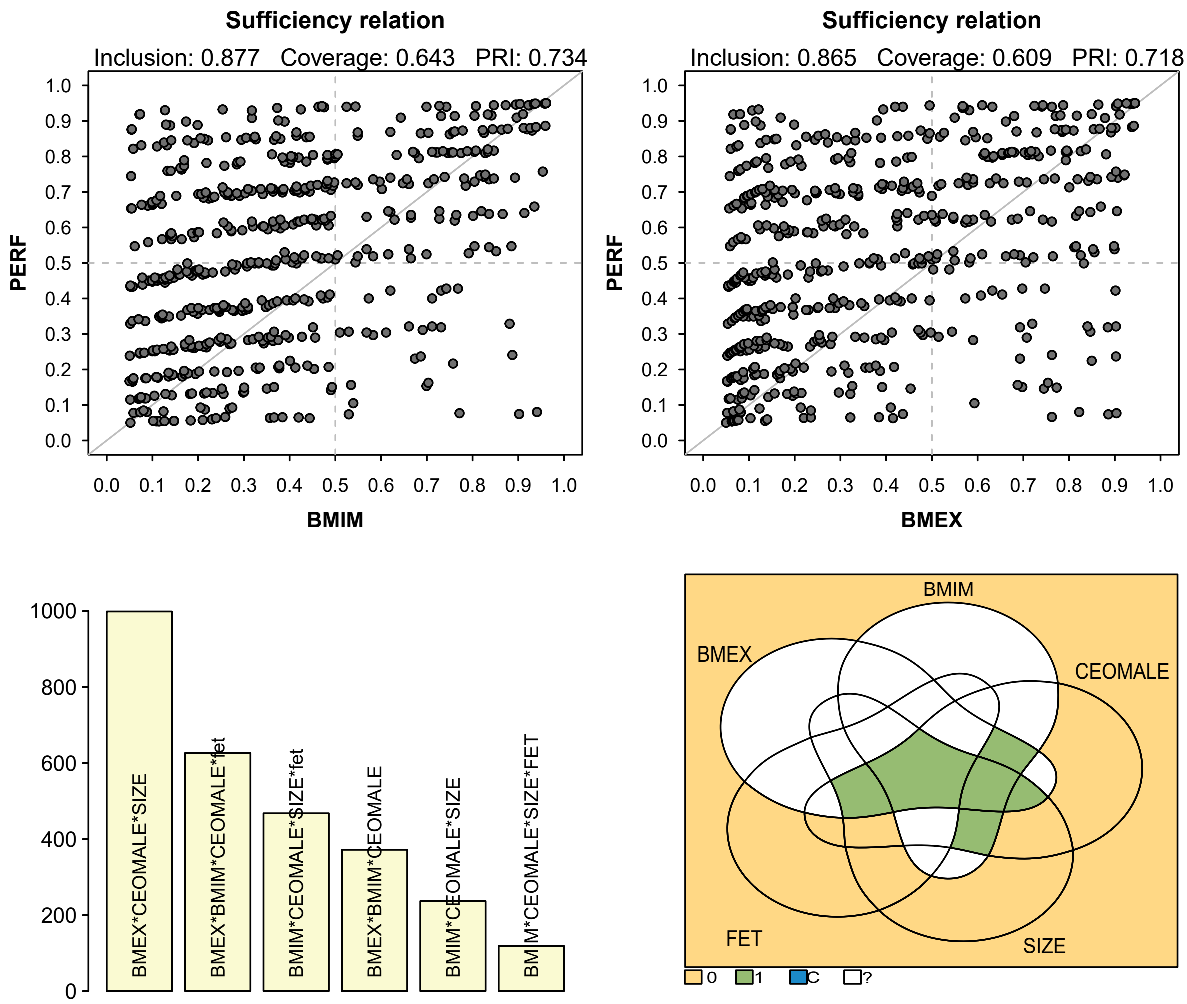


Figure 24 Robustness of fsQCA analysis. Top: sufficiency relation of the PIs after minimization of the truth table with row dominance. Bottom-left: histogram of PIs after 999 iterations of a 90% simulated subsample of the data. Bottom-right: Venn diagram showing the solution of the fsQCA.

After validation of the five-condition model, we added the last firm characteristic, age. We modelled age as crisp condition segregating older firms from younger [STARTUP] firms. The solution obtained has a coverage of 41% and consists of three different causal configurations (Table 20):

```
BMEX*CEOMALE*SIZE*startup + BMEX*BMIM*CEOMALE*FET*SIZE +
```

```
BMEX*BMIM*CEOMALE*fet*size*STARTUP => PERF
```

The first PI reflects larger firms (small or medium) that are old and have male CEOs. The second PI represent larger firms with male CEOs in family enterprises. The last PI depicts young micro firms with male CEOs in non-family enterprises. Consistent with the previous model, no unexpected PIs are found during the iterative analyses at reasonable numbers, providing evidence of robustness (Figure S6). The solutions include firms actively engaged in BMEX and or BMIM, with male CEOs. From these firms, some belong to micro, young, non-family enterprises, while others consist of larger old firms or larger family enterprises.

Frequency cut = 10, Consistency cut = 0.85			Consistency	Coverage Raw	Coverage Unique
1	PI	BMEX*CEOMALE*SIZE*startup	0.86	0.25	0.16
2	PI	BMEX*BMIM*CEOMALE*FET*SIZE	0.9	0.18	0.082
3	PI	BMEX*BMIM*CEOMALE*fet*size*STARTUP	0.94	0.07	0.073
		Solution	0.89	0.41	

Table 20 Solution with all the conditions.

Multi-group analysis

Consistent to what was found during the LCA (Supplement E), the fsQCA identified the firm characteristic size as most dominantly influencing the outcomes. Therefore, firm size was selected as basis for further analysis, and a multi-group comparison was done based on size. For each of the three groups, solutions were found (incl = 0.85, Ncut = 10) for the outcome [PERF] and the negated outcome [perf] (Figure 25).

Intuitively, the solution coverages for the negated outcome explanations are lower than the coverages for the outcome. The combination of the absence of these conditions is not as appropriate to explain low performance as the presence may be used to explain high performance.

The solution coverage is different across groups and increases with size. For the [PERF] outcome, the coverages are 38%, 50% and 56% for micro, small and medium sized firms respectively.

Intermediate configurations for	(1) Micro firms			(2) Small firms					(3) Medium firms				
Configuration	Low PERF	High PERF		Low PERF		High PERF			Low PERF		High PERF		
BMI engagement													
– BMEX	⊗	●	●	⨂	⊗	●	●	●	●	⊗	●		⊗
– BMIM	⊗	●	●	⊗	⊗	⊗			⨂	⊗		●	⊗
Firm characteristic													
– Male CEO	⨂	•	•	•	⨂	•	•	•	•		•	•	•
– Family enterprise	⨂	⊗		●			•			⨂		⊗	●
– Startup (established >2000)			•	●	●			⊗	⊗	●	⊗	⊗	●
Consistency	0.84	0.92	0.94	0.81	0.81	0.91	0.86	0.84	0.82	0.83	0.83	0.95	0.87
Raw Coverage	0.11	0.25	0.27	0.13	0.04	0.38	0.23	0.30	0.34	0.08	0.41	0.25	0.10
Unique coverage		0.11	0.13	0.13	0.04	0.09	0.04	0.06	0.34	0.08	0.21	0.04	0.10
Overall solution consistency	0.84	0.93		0.81		0.86			0.83		0.84		
Overall solution coverage	0.11	0.38		0.17		0.50			0.42		0.56		

Figure 25 Multi-group comparison in fsQCA. Notes: black circles indicate the presence of a casual condition and crossed white-circles indicate the negation of a causal condition; blank spaces signify its absence; large vs. small circles indicate core vs. peripheral conditions.

Within the group of micro firms, it turns out that [BMEX] and [BMIM] are both core conditions in the explanation of the outcome. This suggests that, at the population level, activity in both is needed to obtain high performance. The solution for the negated outcome, which is identified with far less empirical relevance, consists of [bmex] and [bmim], yet they do not fulfil a core condition here. It thus appears that low BMEX and BMIM can result in low PERF but this is no evident link, and gender of the CEO (female) and the classification of a family enterprise (non-family) plays a more thorough role in this regard.

Surprisingly, the group of small firms seems to rely solely on [BMEX] rather than [BMIM] in the explanation of the outcome. Moreover, [bmim] is found in one of the solutions for [PERF]. Thus, BMEX seems to dominate the effect on PERF for the group of small firms.

In the group of medium sizes firms, solutions are found with either [BMEX] or [BMIM] as core conditions or none. [Gender of CEO] is consistently identified as male for the solutions that explain [PERF] but fulfils no core condition. This could be due that solutions with female CEOs might not be identified as their coverage falls below satisfactory values.

Interestingly, in the group of medium sized firms, selection of young family enterprises alone appears to be sufficient for an explanation for [PERF]. Likely, the effect of [STARTUP] gains influence on performance when firm size increases, given that these larger firms had faced more growth in similar timeline.

5.5 Comparison of findings

In the prior sections we have presented the results models and comparisons of data subsamples for three different techniques. Here we compare findings across the techniques. First, the relations of the latent variables to the dependent variable is discussed. Subsequently, the findings of the group comparisons will be compared. Finally, the results of LCA and fsQCA will be compared with mean factor score presentation.

In all techniques, both BMEX and BMIM were found to positive relate to PERF. In SEM, relations were confirmed in the $P < 0.001$ significance level and in addition, BMIM was found to mediate the effect of BMEX on PERF. The LCA revealed initially four latent classes with different activity profiles. When studying the class means, it was found that activity in BMEX and BMIM was associated to a near linear relation with PERF. The fsQCA showed that BMEX and BMIM were dominant conditions for the prediction of the outcome PERF. Similarly, the negation of BMEX and BMIM could explain the absence of high PERF which was consistent with the argument that these latent variables do indeed effectuate PERF.

Next, one could question the empirical relevance of these relations. Although the way this is measured is considerably different among the techniques, and one should never directly compare these numbers, it could be useful to intuit the approximate significance of the findings. For the SEM, it was found that the R-squared for PERF was roughly 20%. In other words, about a fifth of the observed variance of PERF could be explained by the two latent variables BMEX and BMIM. At first sight this number might appear rather low. It is, however, naïve to expect that solely two factors could explain the bulk of the variance of a variable as complex as firm performance. Either would such a result come from a model with low external validity or would the explanatory factors have overlap with the dependent variable, which would make the relevance of such findings questionable. Therefore, we argue that BMEX and BMIM relate to PERF in an extent that is relevant for both theory and practice. The LCA revealed a roughly similar result as the R-squared for PERF was found to be 24% in the base line model. A higher explanation of PERF was found during the fsQCA, since this technique takes asymmetric relations in to account which are applicable to the relations being under the scanner. For example, while high activity in BMEX might result in higher values of PERF, high activity in PERF might be less appropriate to explain high BMEX. To put differently, there can be many factors that explain high PERF, also in the absence of BMEX. Nevertheless, BMEX could still influence PERF since higher values of BMEX might correlate with higher values of PERF. In contrast to SEM and LCA, fsQCA takes this notion in to account and therefore often provides higher numbers of empirical relevance. Depending on the different values for the thresholds, the fsQCA revealed total coverage in the range of 30 – 50%.

A subsequent question was to compare subgroups in the data and investigate how relations may change. In the SEM, we tested the moderating effect of the four firm characteristics by doing multi-group comparisons. Although none of the chi-square difference tests came out to be significant, subtle changes were found. Between the size groups, it was found that the group of micro and medium sized firms had a slight increase in explained variance, and strength of relations on performance when compared to the intermediate size of small firms. Similarly, this effect was identified for firms with female CEO's when compared to firms with male CEO's, and for young firms compared to more mature firms.

During the LCA and fsQCA, we focused on the direct effect of these firm characteristics. When added as covariates in the LCA, differences were observed in probability means of the latent classes. Firms with female CEOs had higher representation in the poor group and lower representation in the good group when compared to firms with male CEOs. Family firms appeared to have higher representation in the excellent class but had also more representation in the fair class and lower representation in the good class compared to the group of non-family firms. The group of young firms had more representation in the poor group compared to the older group, but also had more representation in the excellent class. Between the size groups, a decrease in representation in the poor group correlated with increasing size. However, this relation was not observed when focussing on the excellent group, where micro firms had even higher representation than small firms. Taken this, it was not uncommon for a group to have more representation in both better- and underperforming classes, suggesting a more heterogenic behaviour of the specific group.

Both the fsQCA and the LCA revealed that, among the four firm characteristics under investigation, firm size was the most prevalent. This direct size effect can be composed of an effect for the average size group, where bigger size represents better innovation and performance, and an effect from the best performing firms in each size group, where micro firms perform better or equally as small firms (Figure S7). In the fsQCA, micro firms simultaneously engaged in BMEX and BMIM were identified as configuration with high PERF. In the group of small firms, the role of BMEX appeared to dominant over BMIM, and in the group of medium firms the presence of either one of the two resulted in configuration with high PERF. Apart from the characteristic firm size, the gender of CEO (male) appeared frequently in solutions explaining high performance.

5.6 Applicability of findings

Our results show that BMEX and BMIM lead to PERF, and that these relations (moderating effect) and the activity (direct effect) therein can depend on the characteristics of the firm. To clarify these insights for policy makers, we aim to overview configurations based on their average BMI activity and performance. A way to do this is by plotting configurations with their average activity for BMEX, BMIM and PERF (Figure 26).

Configurations are abbreviated by three characters depicting gender of CEO (M: Male, W: Female), label of family enterprise (F: Family, N: Non-family) and age (Y: Young, O: Old). This visualization makes it convenient to depict configurations that deviate from the pattern. For instance, the configuration Medium-WFY, is by far the most engaged in BMEX and BMIM and has the highest PERF but has a very low population of 3 respondents. Groups with so few respondents are too small for reliable computation of the mean and have negligible effect on results obtained. Yet this visualization helps to identify them and to select these respondents, for example, for further investigation in qualitative studies. Medium-WNO, representing 12 respondents, is another interesting configuration as it reports high means for BMEX and BMIM but relative low PERF. Such a group might be interesting for further investigation, or as target group for longitudinal studies. One should be cautious, however, with the interpretation of means when the group size is insufficiently large. It could thus serve best as back-verification of obtained results rather than as method for quantification.

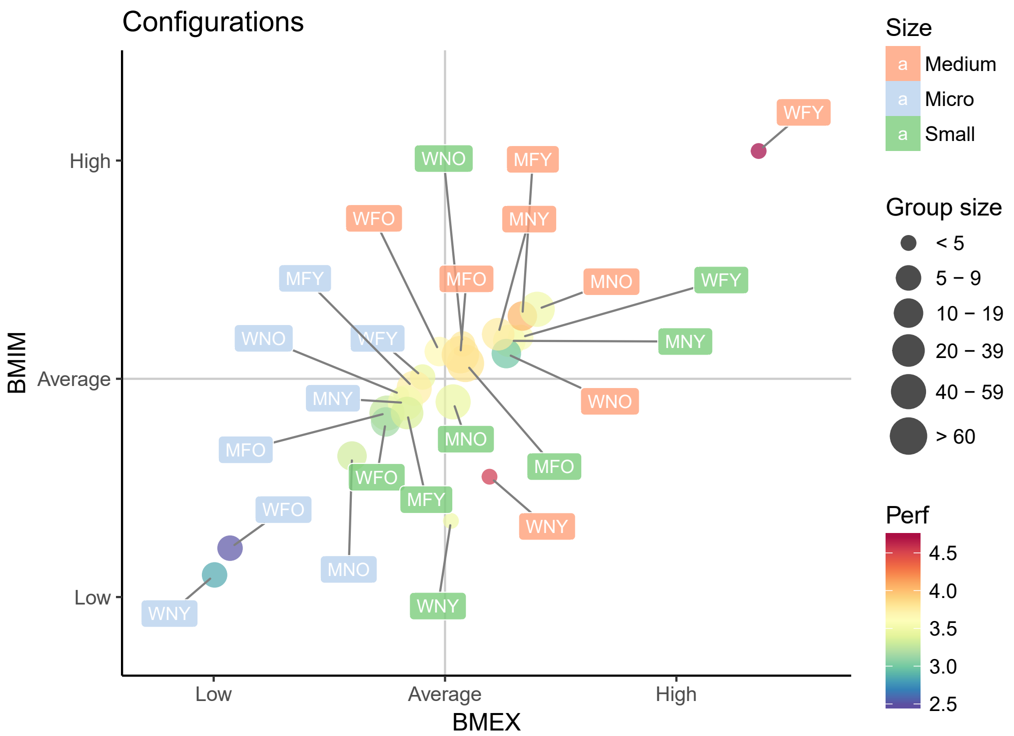


Figure 26 Classification of configurations based on BMEX, BMIM and PERF (color). Sizes represent the relative sizes and label colors depict size classification of firms.

The most thriving configuration represents young medium sized firms with female CEOs. Firms with these characteristics may be studied in further depth as they could serve as visionaries that inspire others. On the other hand, configurations that on average reported lower activity in BMI engagement were observed with lower satisfaction in average performance (Figure 26). One should be aware that this representation involves average numbers. Obviously, great differences are observed at the single case level. A closer look at the factor scores could provide insights to demonstrate the variance at the single firm level (Figure 27).

If policy makers want to take actions that boost the economy, they should focus on the firms that report below average numbers for performance. Since we are interested in the effect of BMI engagement on performance, it makes most sense to focus on those firms that report low performance and have low BMI engagement. This group could be targeted by focussing on the bottom left square in the scatter plot. From this group, most of the firms report below average firms. If now poor configurations are marked on the group of below average performing firms, these configurations are overrepresented. The firms with below average performance in the square consist of about one fourth of the firms, while these configurations are represented in about one third. The three configurations together explain about one third of this target

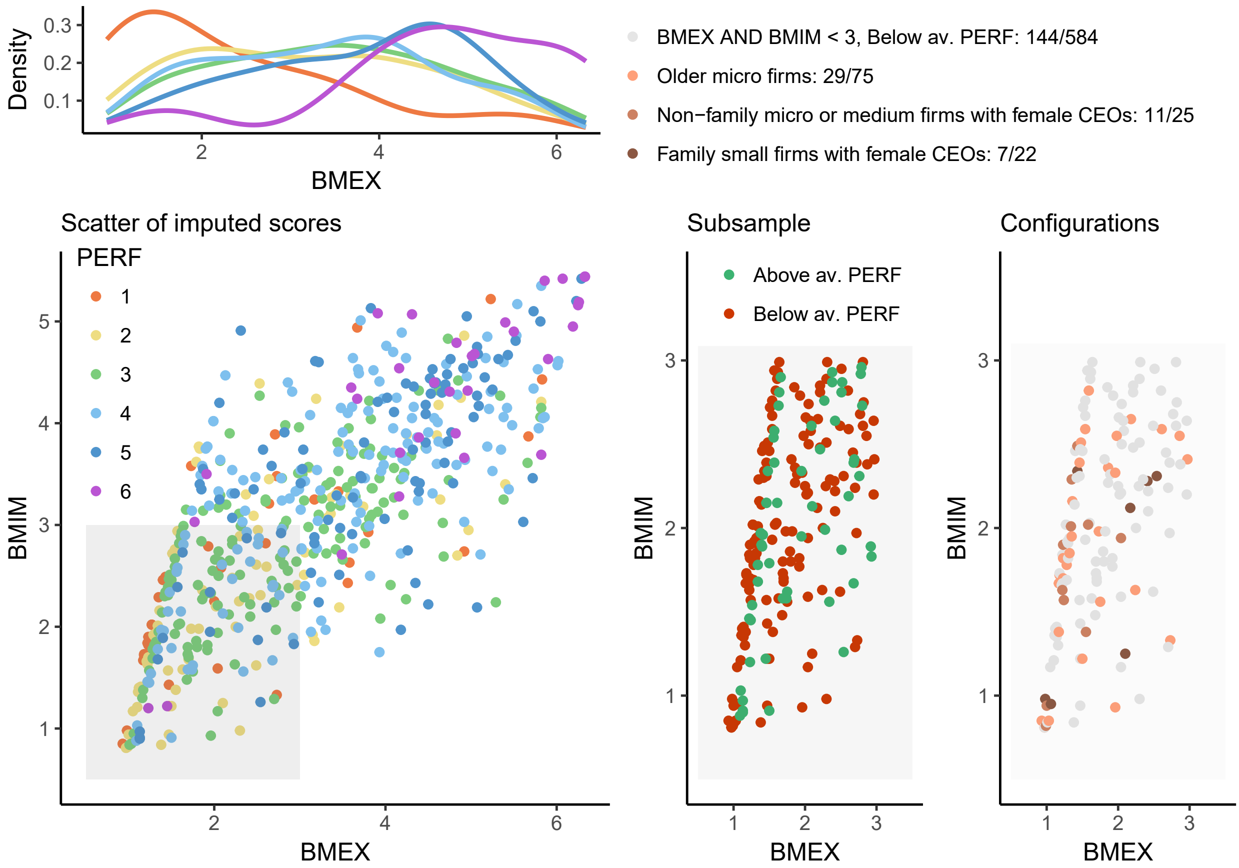


Figure 27 Applicability of results. Scatter of imputed factor scores. Firms with scores of BMEX and BMIM below 3 are dominated by firms with below average PERF. Poor performing configurations partly cover the underperforming subset.

For policy makers, it can be valuable to combine findings on BMI activity with numbers for economic appearance and relevance (Table 21). This may help to place the observed differences in context. While some configurations in the group of micro firms occur rarely in the data, they could still contribute to more economic added value compared to configurations in the group of small and medium sized firms, since micro sized firms appear more frequently in the economy. For example, young micro sized firms with male CEOs consist of almost half of all the registered firms.

Taken this, our results can be used to target firms based on there BMI engagement. Subgroups that perform well in this regard can serve as inspiration for others, while subgroups that show a low engagement can become the focus of actions aimed at raising awareness of BMI practices.

#	Size	Characteristic	N	AV. BMI activity	AV. PERF	AV. BMI label use (%)	Size BA LC (%)	Membership BA LC (%)	Appearance* (% firms)	added value* (% of total)
1	MI	Female CEO	29	–	–	34	28	44	15	3.3
2	MI	Old ∩ Female CEO	13	–	–	31	28	32	6.6	1.5
3	MI	Non-family	76	–	+/-	39	28	29	38	8.6
4	MI	Young	107	-	+/-	38	28	29	54	12
5	MI	Young ∩ Male CEO	91	+/-	+/-	38	28	26	46	10
6	SM	Non-family	87	+/-	+/-	34	14	16	2.4	7.5
7	SM	Female CEO ∩ Family	22	+/-	+	31	14	12	0.6	1.9
8	SM	Female CEO ∩ Non-family	13	+/-	+/-	31	14	15	0.4	1.1
9	SM	Young	77	+/-	+/-	39	14	9	2.2	6.7
10	ME	Family ∩ Male CEO	72	+	+	39	13	16	0.4	7.6
11	ME	Older ∩ Female CEO	23	+	-	35	13	15	0.1	2.4
12	ME	Non-family ∩ Female CEO	13	+	–	31	13	12	0.1	1.4
13	ME	Young ∩ Female CEO	3	++	++	**	13	12	0.02	0.3
14	ME	Non-family	87	++	+/-	45	13	10	0.5	9.2

Notes: Micro (MI), Small (SM), Medium (ME) size classification. AV: average, BA: below average, LC: latent class. +/- represents -5% till +5% deviations; - equals -10% till -5%; – below -10%; + depicts 5% - till 10%; ++ means above 10%. *Estimate based on the subsample frequencies in the data multiplied by the size dependent characteristics of SMEs in the EU-28 non-financial business sector. **Only 3 respondents, from which 2 used BMI label.

Table 21 Overview of notable configurations with BMI activity, performance implications and economic relevance.

5.7 Validity of findings

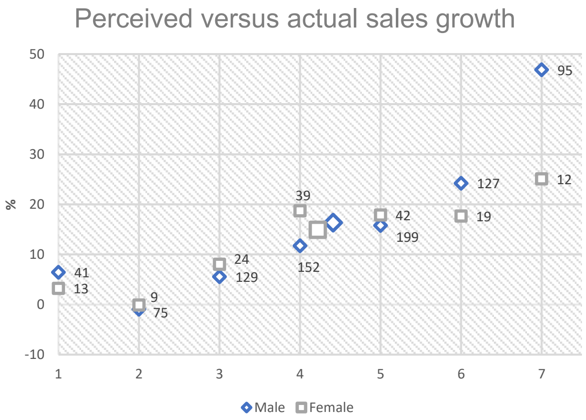
Throughout the study, multiple assumptions were made that may affect the validity of results. Two major assumptions concern the use of perceived performance instead of actual performance indicators and the use of screener questions as inclusion criteria. Below, we will criticize these assumptions and investigate the potential bias of these assumptions.

Perceived performance

In Section 5.1, it was shown that the distribution of perceived performance deviated from the numbers of actual performance. To provide insights on the relation between these two, average values were collected for the respondents that reported equally on the perceived indicators. Further, one firm characteristics (gender of CEO) was used to compare two groups, enabling to see whether this relation may be affected by the characteristics of the firm (Figure 28).

Firms with male CEOs reported perception indicators with more correlation to actual increase than female CEOs did. For the sales growth indicator, both groups showed behaviour with reasonable correlation to actual numbers. However, for the profit growth indicator, this relation was less evident, and in the group of firms with female CEOs, no clear increase was observed between Likert responses above 4.

Although this visualization involves average numbers, which can be problematic for such a heterogenic population, it does indicate the sensitivity of bias that may be introduced when using perceived indicators. On the other hand, one most consider that a manager's response to such a question may include more information than a single financial ratio may have. It remains difficult, therefore, to state that one approach is superior to the other. Nevertheless, it should be clear that these terms are not interchangeably.



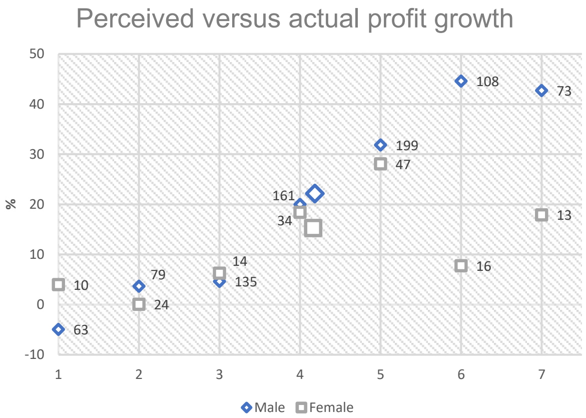


Figure 28. Gender-dependent bias of perceived performance. Real versus perceived performance. Big markers represent average numbers for the firms with male (blue) and female CEOs (grey).

Screener questions

As mentioned in Section 5.1, only 38% of the firms that made BM changes did label these changes as such. One may question what constitutes to BM changes and what does not. The current study was based on four screener questions to answer this question. Firms were included for analysis when at least one of the four screener questions was answered positively. Most of the firms met multiple screener questions simultaneously, but a considerably part of the respondents (27%) did report positively to solely one of the screener questions (Figure 29). This group (27%) enables to compare the effect of individual screener questions on results.

It may be that not all questions are as strict and that some might be more sensitive to inclusion of false positives than others. To demonstrate this, we compared correlations between the two latent variables (BMEX, BMIM) and the dependent (PERF). As can be seen from Table 22, considerable differences in Pearson correlation coefficients are observed, which suggest that questions S2C and 2CD permeate more in the outcome than S2A and S2B.

Obviously, a sound theoretical basis is most important for the establishment of proper inclusion criteria. However, these results indicate that composition screener questions can considerably influence the outcome of findings.

Further investigation in this regard can help to clarify these differences and perhaps alternative inclusion criteria can be investigated, such as limiting inclusion to firms who report positively to at least two questions.

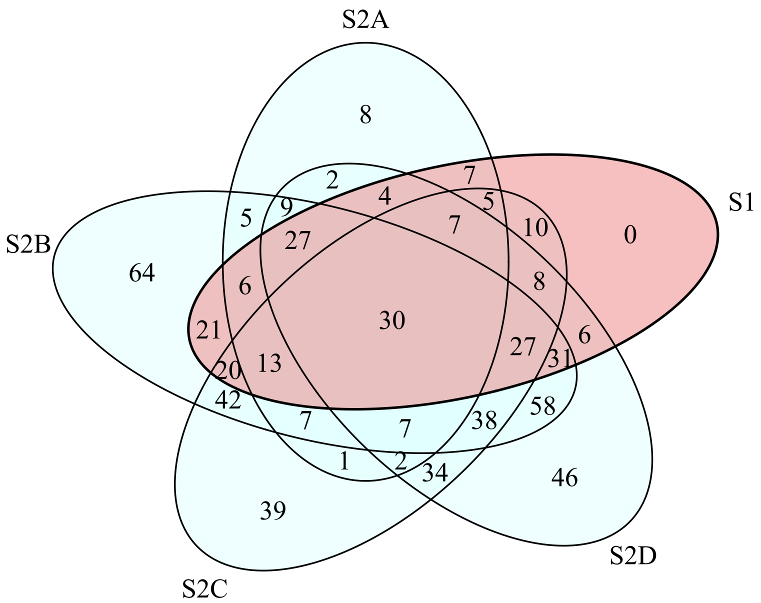


Figure 29 Bias of screener questions. Venn diagram denoting the number of companies in intersection areas of screening questions. Companies are selected for inclusion when agreeing to one of the four S2 questions.

Subset	cor(PERF, BMEX)	cor(PERF, BMIM)	N	%
S2A = 1 ∩ S2B = 0 ∩ S2C = 0 ∩ S2D = 0	-0.22	-0.51	8	1.4
S2A = 0 ∩ S2B = 1 ∩ S2C = 0 ∩ S2D = 0	0.3	0.38	64	11
S2A = 0 ∩ S2B = 0 ∩ S2C = 1 ∩ S2D = 0	0.47	0.39	39	6.7
S2A = 0 ∩ S2B = 0 ∩ S2C = 0 ∩ S2D = 1	0.46	0.47	46	7.9
S2A = 1 ∩ S2B = 1 ∩ S2C = 1 ∩ S2D = 1	0.54	0.52	37	6.3
Total sample	0.42	0.43	584	100

Table 22 The effect of inclusion criteria. Subsets of the data with the Pearson correlation scores for the latent variables measured against the dependent variable.

Chapter 6 Discussion

Chapter 6 will summarize the findings of this study and discuss their implications. Main findings of three different techniques will be reported and discussed. Implications of the study will be discussed from an academic and managerial perspective. More specifically, academic contributions will be separated in a section on BMI literature and in a section concerning methodological aspects. In the following section, it will be argued what recommendations could be derived for BMI-related policy making. Finally, the limitations will be discussed, and suggestions will be given for further research.

6.1 Answering the research question

In Chapter 5, findings have been presented from different techniques. Here, we will discuss these findings with respect to the sub questions that they apply to. In Chapter 1, five research questions have been proposed. Below, these questions will be touched upon in that order.

The first sub-question was proposed to overview related work and to place to current study in perspective. We have discussed recent reviews from Foss & Saebi (2017b) and Wirtz et al. (2016) to illustrate the variety of different approaches that scholars use to study BMI. More specifically, we have focused on empirical studies and contrasted studies that view BMI as organizational process to those that see BMI as an outcome. Following the first group, we have argued to study BMI as a process because the results of this approach can provide strong managerial relevance. Next, an overview was given on different ways by which the BMI process can be conceptualized. For clarity, this study simplified the process to two phases – BM experimentation and BM implementation, that recur in different studies (e.g. Enkel & Mezger, 2013; Geissdoerfer et al., 2017; Girotra & Netessine, 2013; Sinfield et al., 2012). These were thus selected to represent the process of BMI and were used to answer subsequent questions.

The second sub-question revolved around the BMI engagement of European SMEs. Surprisingly, BMI has not reached many SMEs and from those that conduct these practices, few acknowledge this as such. Based on cross-sectional data gathered during the ENVISION project, it was found that 37% of the European SMEs made changes to their BM in the past two years. From that group, only 38% labelled these changes as BMI, which illustrates the lack of awareness in SMEs. This study focused on those that made BM changes (37%), and continued analysis on this group of firms.

The third sub-question covered the role of structural firm characteristics on BMI engagement. We focused on the direct effect of four characteristics, namely firm size, firm age, gender of CEO and classification into family and non-family enterprises. Using a clustering approach, LCA was used to clarify the effect of these characteristics individually. We identified two types of effects. The first, most obvious, was found when studying the firm characteristic gender of CEO, where firms with male CEOs had lower representation in the poor performing classes and higher representation in the good performing classes. The second, more complex effect, was found during investigation of the other three characteristics. Here, we found contrasting findings, where a characteristic could cause a higher representation in more extreme classes, reducing the representation in the moderate performing classes. For example, younger firms were found to have a higher representation in the poor and excellent classes compared to more mature firms. Thus, direct effects of these firm characteristics were considerably identified, yet it appeared that within the population of firms having such a characteristic (for example: young firms), different parts were present that caused conflicting behaviour at the single characteristic level. Therefore, we continued the analysis by studying multiple characteristics simultaneously during the fsQCA.

During the fsQCA, multiple configurations were found to associate with BMI engagement and high performance. We found that activity in BM experimentation and BM implementation are good predictors for a firm to have high firm performance. Apart from that, bigger (small or medium) SMEs with male CEOs were frequently identified as solution for high performance. However, we also found the solution involving young, micro firms with male CEOs in non-family enterprises (Table 20). Taken this, when characteristics are added simultaneously, the dependencies of characteristics are encountered, revealing more specific behaviour of certain sub populations. In turn, this can be used to provide insightful overviews for policy makers (Figure 26).

Thus, this question can be answered by stating that firm characteristics do indeed influence BMI engagement in Europeans SMEs. However, the heterogeneity that is still involved in such a subpopulation, supresses the observed effect when studied at the single-characteristic level. By adding more characteristics and thereby narrowing the subpopulations, these effects can be better understood and unravelled.

The fourth sub-question concerned the effect of BMI on firm performance. We used a SEM analysis to measure the causal effect from BM experimentation and BM implementation on firm performance. Our results show that both practices can lead to firm performance. Moreover, we confirmed a mediating role for BM implementation, strengthening the effect of BM experimentation on performance. These results support the idea that BMI is conducted through a process consisting of different phases and that engaging in BMI has a positive effect on business performance.

			Based on		**Raw data**	**CFA factor scores**		
SQ	H	Type	Relation	Theory	Descriptive	SEM	LCA	fsQCA
1		Literature	Link between BMI and PERF					
2		Descriptive	Average BMI engagement					
3		Explorative	Difference in BMI engagement dependent on firm characteristics					●
3		Descriptive					●	
4	H1	Confirmative	Changes OM -> Changes EA			-	●	●
4	H2a,b	Confirmative	BMEX -> PERF			●	◑	
4	H3	Confirmative	BMEX -> BMIM			●		
4	H4a,b	Confirmative	BMIM -> PERF			●	●	●
4	H5a,b	Confirmative (Mediation)	BMEX -> BMIM -> PERF			●		
5		Confirmative (Multi-group)	Significant relation differences between subgroups?			○		

● Supported; ◑ Partially/Conditionally supported; ○ Not supported; - Not measured; x Counter evidence.

Table 23 Answering the main research question.

The fifth sub-question asked whether the firm characteristics influence these relations. Independent of firm characteristic, the effects were identified as significant, indicating that these effects are robust and hold for different subpopulations in the dataset. Next, the moderating role of the firm characteristics was being investigated by doing multi-group comparisons. Although we did not find significant differences when performing chi-square difference tests, we did observe some subtle differences when focusing on specific relations. For example, for firms with female CEOs, we found stronger effects from BM experimentation and BM implementation on performance. Likewise, we found stronger effects on performance for micro and medium firms compared to small firms. Taken this, we do observe some moderating effects from the four firm characteristics.

In Chapter 1, the main research question was proposed as following: To what extent does BMI engagement enhance business performance in European SMEs? During this study, we used different techniques to answer the sub-questions (Table 23). In sum, we can answer the main research question by stating that BMI engagement, by which we refer to as the act of being involved in the process of BMI, indeed leads to firm performance. Firm characteristics influence BMI engagement both in a direct and moderating manner, where the former results in most dramatic effects. Therefore, differences are observed between subpopulations of SMEs. Since the SMEs that are active in these process constitute to only a small part of the European SME economy, their remains valuable opportunities to increase this number and contribute to economic growth.

6.2 Theoretical contribution

Empirical findings from this study contribute to our understanding of BMI. As pointed out by Foss and Saebi (2017b), few articles look rigorously at the performance effect of BMI.

The findings of this study support the argument that BMI engagement, which we refer to as the level of BM experimentation and BM implementation, has a positive effect on firm performance. Thereby, this study provides evidence for the view that the act, or process of BMI positively affects firm performance. These results are consistent with findings from Aspara et al. (2010b), who found that firms with strategic emphasis on BMI exhibit higher profitable growth. Moreover, they support the findings from Cucculelli and Bettinelli (2015), who investigated Italian SMEs and identified a positive effect of BM changes on the ability of a firm to perform well.

Interestingly, our results suggest that dedicating resources to BMI is sufficient to improve the performance of the firm as perceived by the SME manager. This differs from the view that only “successful” efforts cause this effect, and that poor execution of BMI practices leads to failure rather than success (Chesbrough, 2010; Friedrich von den Eichen, Freiling, & Matzler, 2015). Obviously, implementation of unfeasible BMs leads to failure, not success. However, dedication of resources to BM experimentation may help to investigate several alternatives and improve the changes for BMI to succeed.

We are, to our knowledge, the first to show that consecutive phases in the BMI process can strengthen firm performance independently. The mediating role of BM implementation suggests that innovation of BMs involves separate, causally linked practices. Until now, most scholars have approached the complex link of BMI to performance by investigating different outcomes, such as competitive advantage (Wirtz & Daiser, 2017) and innovativeness (Molina et al., 2017). In contrast, we limited the focus to one dependent variable and studied this complex link by modelling BMI as concept with separate phases. There exist various ways by which this approach could be extended, as can be seen from the variety of conceptualizations that have been proposed to capture this process (Table 5). However, increasing detail can reduce the external validity, because BMI can be practiced in different ways.

One advantage of conceptualizing BMI by multiple concepts is that it enables more thorough investigation of the role of moderators. In this study, the selection of moderators was limited to tangible firm characteristics because they can be easily targeted in programs developed by policy makers. The same approach may well be used to clarify the role of other moderators such as organizational capabilities.

Our results show that the four firm characteristics (size, age, family and gender of CEO) can considerably influence BMI engagement. We identified complex differences at the single-characteristic level, indicating the heterogeneity still present in subpopulations with a specific characteristic.

We found that smaller firms are more often less engaged in BMI practices, which may be caused by the lack of available resources for BMI (Ruzzier & Ruzzier, 2015). This pattern was not found when the population was clustered in LCA and only the firms in the excellent class were considered, where micro firms and medium firms had higher representation than small firms. Likewise, in the group of micro and medium firms, the SEM revealed a stronger moderating role from BMI to performance, when compared to the group of small firms. These results supports the view that the relation between innovation and firm size is U-shaped (Acs & Audretsch, 1988). However, in the context of SMEs, most firms are still not heavily engaged in BMI practices, which may be why the inverse linear relation is dominant at the population level.

Further, we found that SMEs with male CEOs are more engaged in BMI than firms with female CEOs. However, when firms with female CEOs engage in BMI, they perceive a stronger effect on performance than firms with male CEOs. These differences might be caused by gender-dependent differences in risk-aversion (Zeng & Wang, 2015) or entrepreneurial orientation (Bae et al., 2012). These findings bring up the question whether gender dependent barriers to BMI are present in European SMEs and why female CEOs may be more reluctant from investing in BMI.

Younger firms had more representation in the poor and excellent class compared to more mature firms. This result may resemble the difference in stability between these groups. Firms in start-up phase may represent a more heterogenic population and generally map on the extremes of BMI engagement level.

Finally, non-family firms were often more engaged in BMI than family firms. This difference may be due to educational differences of the CEO, or from differences in management training activities (Smith, 2007). When clustering the data, family firms were more represented in the highly engaged (excellent) class compared to non-family firms.

Together, these findings contribute to our understanding of BMI engagement in SMEs and how this differs depending on structural firm characteristics.

6.3 Methodological contribution

This study offers an innovative analytical approach to obtain insights from the data in a comprehensive manner (Figure 30). Combining three different techniques enables to test different aspects related to the same basic conceptual model.

SEM remains a widely recognized method, especially for hypotheses confirmation of conceptual models. The LCA provides insights from the underlying structure of the data and exposes different behaviours in clusters. Other than manual multi-group comparisons, the SEM analysis cannot include this and LCA may thus be a valuable extension of the analysis. When multiple covariates are to be tested and compared, the LCA may fall short for this purpose. Although we did experiment with a way to use the LCA for this purpose (see Supplement E), this might not be the most adequate manner. FsQCA can be used to explore configurations when multiple conditions are being compared. One additional advantage of the fsQCA is that it encounters asymmetric relations which is not done in SEM. This can provide strength to findings, especially when complex dependent variables are used that have a low explained variance in SEM.

Nevertheless, a combined use introduces some additional problems. All methods relied on the imputed factor scores from the CFA and for the LCA and fsQCA an additional manipulation was required. We chose to use the imputed factor scores over alternatives, such as taking the mean, since this enabled compensation for common method bias. Since the range of factor scores can depend on the number of construct items, different ranges will be produced for the latent variables. To account for this, an additional compensation is needed during the fsQCA calibration, which is not ideal. Furthermore, rounding factor scores as preparation for LCA may have a limitation as well. The extreme integers contain only values from one side (e.g. value 7, 7 > 6.5) while integers in between contain scores from two sides (e.g. value 6, 6.5 > 6 > 5.5). However, the compensation of common-method bias outweighs these effects, and therefore this approach was preferred over taking averages.

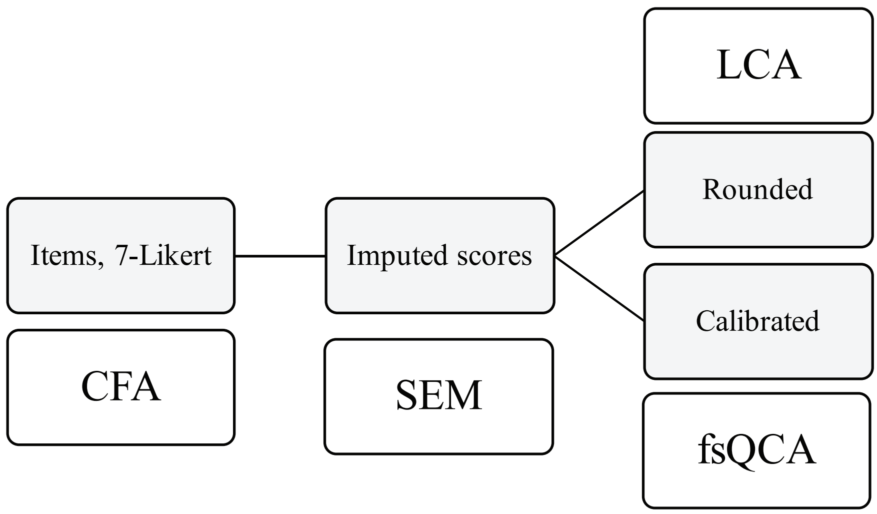


Figure 30 Methodological approach. Schematic diagram indicating the data flow for each of the techniques.

While the combined use of these methods enables extension of analyses, it also helps to gather corroborative evidence. Table 24 lists some of the main findings with the contribution from different techniques. As can be seen, all techniques provide evidence for the relations under investigation. In contrast to SEM, the LCA and fsQCA offer nuanced findings where statements can be conditionally supported.

6.4 Implications for policy making

Our study shows that allocation of resources to BMI, which we refer to as BM experimentation, has a positive impact on performance. We demonstrate that BM experimentation drives changes in the BM by altering the Operating Model and the Enterprise Architecture, which result in a positive effect on perceived performance. SME managers need to recognize the need for BMI to improve their performance. Particularly, this advice should be given to the bulk (63%) of SMEs that did not make changes in the BM in the past two years and were therefore not included in the study.

The results have implications for policy makers too. European policy makers have recognized the importance of BMI for economic growth and included BMI in Europe-wide funding programs, such as in the H2020 project (EC, 2011). Our study proves that dedication of resources for BMI contributes to performance, a finding that lend support to their actions. Since the studied population contains a heterogeneity that is characteristic for the European economy, i.e. with all sectors and from different countries, the results apply to the European SME economy as a whole.

One of the actions that needs further attention is to raise awareness about BMI and lower the barriers against BM experimentation. Our results suggest these efforts should particularly be focused on the smaller SMEs, i.e. the micro sized and small sized SMEs. In addition, we found that firms with female CEOs report on average a lower engagement in BMI and satisfaction with performance. These notions could help to narrow the focus and to dedicate efforts in a more meaningful way.

More specifically, awareness could be enhanced in a subgroup by launching events and workshops. For this purpose, policy makers may want to focus on rare subgroups.

While the concept of BMI has gained considerable attention in the last decades, in the context of SMEs, the notion of BMI is still new and most of the SME managers are not involved in BMI activities (63%), and only a small group of SMEs is involved in BMI and recognizes it activities as such (15%). The importance of policy makers in their role to raise awareness and assist SMEs in these activities is imperative and could result in a stronger economic environment in the long term. An evident strategy could be to focus on subgroups that report low activity and dedicate resources to raise awareness in these groups. While our study has overviewed some characteristics that could be used to detect differences, further studies will be necessary to investigate interdependencies with other characteristics and to validate findings on other populations. The decision to focus on a near representative population of the European SME economy has strengthened the external validity of our findings, but also created a wide diversity of firms which resulted in a high variance that is left unexplained.

		SEM	LCA	fsQCA
Latent variables	Firms that actively engage in BM experimentation experience positive effect on their perceived business performance	●	●	●
	Firms that actively engage in BM implementation experience positive effect on their perceived business performance	●	●	●
	BM implementation mediates the effect of BM experimentation on perceived business performance	●		
Firm characteristics	Firm characteristics have a moderating effect on the relation of BMI engagement to perceived business performance	○		
	Firm characteristics have a direct effect on BMI engagement		●	●

● Supported; ◑ Partially/Conditionally supported; ○ Not supported; x Counter evidence

Table 24 Selection of findings and contribution of different techniques.

6.5 Limitations

The presented study has several limitations. Some can be derived from constraints of the data, some from restrictions in operationalisation and others resulted from methodological decisions and assumptions. We will elaborate on limitations of these types in this order.

Dataset characteristics

Constraints of the data resulted in different limitations. The most important being the cross-sectional nature of the data, which means no information was collected along a temporal dimension. A longitudinal study could enlighten causal relations over time and evidently prove the direction of causality, which remains a topic of discussion when the study is solely based on cross-sectional data. Higher performance may lead to more resources being available for BMI practices, which contributes to the issue of reverse causality.

BMI is a complex concept that can be time consuming and implications may not be directly detectable. Fairly obviously, allocation of resources to BMI might not result in increased in performance in the same year. A longitudinal study could reveal BMI implications along a temporal dimension and would thus be preferred. Although project ENVISION, which collected the data used in this study, intended to collect data for a panel study, the sample size came out to be too small for growth model studies or cross lagged panel studies.

Another limitation that is associated to the data is the sample size. The data used in this study contained detailed information from over five hundred SMEs in Europe. Although this number is rather large for traditional SEM studies, it should be increased to enhance the validity of the multi-group comparisons. Since the population is very heterogenic, researchers may be interested to focus on a specific firm characteristic or sector to lower the variance between respondents. When the focus is narrowed to firms with a set of firm characteristics, numbers become too low for accurate comparison. The sample size should be increased to accurately compare configurations and allow researchers to narrow their focus to a specific part of the population.

Thirdly, single informants were used to collect the data from the SMEs. In the context of SMEs, it is often difficult to find multiple qualified respondents, especially for topics as complex as BMI. Micro or small firms might simply not have multiple employees that make decisions regarding BMI. Consequently, a limitation of our study is that the data is obtained from single informants. To accommodate with this problem, we tested the model for common-method bias. We did find a significant shared variance between the investigated items, which brought us to retain the common latent factor during the CFA. This manipulation of the data minimizes the bias originating from common method bias, but a situation where the shared variance is insignificant would be preferred.

Fourthly, information was collected only when firms passed the screener questions. Multi-group comparisons and causal relations were thus performed on the group of SMEs (37%) that did make changes to their BM. Indeed, the questions under investigation are most relevant for this group and it thus makes sense to focus on this group. However, it would be valuable to compare the findings to the group of SMEs that reported not to be engaged in BMI. Especially for the multi-group comparisons, it would be a good practice to repeat analysis on SMEs that are not engaged in BMI. The findings of our study reveal information about the intensity and satisfaction of BMI engagement between subgroups. Analysis and comparison with the group of SMEs that are not engaged can shed light on frequencies of BMI engagement between subgroups. This might be of special interest for policy makers that pursue a strategy to enhance awareness for BMI.

Restrictions to operationalisation

Apart from the limitations that result from the structure of the data, limitations have arisen from the available items in the data. Ideally, a researcher establishes its operationalization on its own preferred assumptions rather than on a dataset that has already been constructed by others.

As argued throughout this study, the dataset of ENVISION contains an interesting combination of BMI-related items that provide sufficient information for fruitful operationalizations of BMI. However, some critical notes can be made regarding additional information that could have been collected.

Firstly, the dataset consists of more than hundred items that originated from different research intentions. Consequently, several constructs have overlap in their meaning and cannot be properly combined in different models. Relatedly, within similar construct, some questions seem to a lack a prior established purpose regarding their measurement form (reflective/causal-formative/composite). This leaves researchers some flexibility in the CFA, but ideally this would be clear at the start of data collection and this flexibility would be absent.

Secondly, the operationalization here assumes a process-oriented view on BMI and is dominantly focused on early phases of this process. In other words, more advanced phases or more radical forms of BMI are not properly captured in this regard. While many scholars support the view that essential dimensions of BMI as described by Teece (2010) include innovation in value creation, proposition and capture, our operationalization does not include these aspects. Although the dataset contains questions that may be used in this regard (Q2_1 – Q2_10), they originate from different sources and fail to load on a construct in a satisfactory way. It would be interesting to add such an operationalization of BMI to the two previous phases and obtain a three-phase model of BMI (Figure S8). If BMI is to be modelled as solely one construct, the operationalization of value creation, proposition and capture might be most appropriate to capture the concept. An operationalization in this way has recently been proposed and involves the establishment of a third order factor (Clauss, 2017).

Thirdly, the used operationalization includes to conflicting perspectives of the literature. While BM experimentation is measured as “act”, referring to dedication of resources to the activity, BM implementation is measured as “outcome”. This limits the validity of the claim that BMI consists of separate phases that interact with performance. Preferably, both phases would be measured in the same manner, and operationalization of BM implementation would be adjusted to the format of BM experimentation.

Methodology

Finally, a group of limitations come from the methodological approach and decisions that were made along the way.

We have chosen to focus on two initiating phases of BMI and relate these to implications on perceived performance. BMI involves BM experimentation and BM implementation, but the concept represents more than solely these two practices. It was beyond the scope of this study to investigate more advanced phases of BMI, or to investigate what factors drive activity of these phases. We are aware that BMI can be operationalized in a variety of different ways. In the literature, the debate continues about what constitutes proper operationalization of BMI and different avenues are currently explored to provide insights on this aspect of measurement (Clauss, 2017).

Another limitation lies in the measurement of the dependent variable. Business performance was measured by perception scales rather than by actual financial ratios. The rationale behind this was that financial ratios might be strongly dependent on the SME’s context, such as industry, size, etc. Using real numbers for performance evaluations would make it problematic to compare SMEs. It should be clearly noted, however, that perceived business performance does not equal actual business performance, and further investigation is needed to unravel these differences in this context.

Lastly, we have chosen to focus on the imputed factor scores as a basis for the three different techniques. The rationale behind this was that this maintains similarity across methods since in SEM this is used as default. In addition, it provides compensation for the common method bias that was identified during the CFA. To our knowledge, however, this is not a very common way for LCA and fsQCA practices and we encountered some problems because of this decision. For the LCA, a discretization is required, which was enabled by rounding to the nearest integer value. Since the number of items can affect the range of the factor scores, six categories were created for two of the latent variables while one was limited to five categories. Alternatively, one could have chosen to use the average value of depicted items, which would have probably resulted in seven categories for all the latent variables. For the fsQCA, a calibration is required that recodes the scores to a range between zero and one. The different ranges in factor scores that resulted from the regression imputation brings difficulties to this process too. We felt justified to adjust the maximum value of the calibration function to the maximum value of the respective latent factor, which allows all the latent variables to have scores that are fully in the fuzzy set. This additional manipulation would not have been needed when the ranges would have been similar for all the latent variables.

6.6 Outlook

The presented study has thrown up several questions in need of further research. Some of which can be assessed by ENVISION, others that require different approaches and demand investigation from novel studies.

Recommendations for Envision

The ENVISION project has collected data on an interesting set of BMI items. During this study, the database has been extended by a new wave of respondents increasing the sample size to over thousand respondents. A natural progression of this work is to repeat the multi-group comparisons on this larger data set, and to explore potential differences. The enhanced sample size will help to obtain higher validity for the multi-group comparisons.

The presented findings suggest that BMI engagement across subgroups can be different between clusters engaged in BMI and clusters that are not engaged. For example, it was found that micro and medium sized firms tend to outperform small sized firms in the excellent latent class, but the summed representation in underperforming classes was highest in micro sized firms. It would thus be interesting to repeat comparisons while performing regressions for ranked subsamples of the data, e.g. by cutting sorted factor scores in quintiles.

Apart from the items used in this study, the ENVISION data contains items on several interesting concepts that could be used for follow-up studies. As mentioned earlier, one direction would be to extent the current model with the phase of BMI referring to completed BMI practices. This phase could be measured using a MIMIC-model, where the BMI components as described by Teece form the BMI phase (Figure S8). When this direction is to be explored, it might be interesting to study different operationalizations of the dependent variable. The data contains several items on perceived performance, which can be combined in multiple ways. During a preliminary analysis, we found that items for financial growth contrasted with items referring to the financial position and that an advanced phase of BMI has a stronger effect on the latter operationalization. This may suggest that firms with completed BMI cycles may be more satisfied with their current financial position, while firms that are in the process of BMI may be more satisfied with their financial growth. Although this question deserves attention from a longitudinal study, further work on the ENVISION data may unravel some interesting insights on this issue.

A different avenue would be to explore factors that explain the performance implications and observed differences between subgroups. Ultimately, this would give insights on how BMI practices result in an effect on performance. Possible areas of interest include the role of BM tooling, organizational culture, and novelty of implemented BMs on the phases of BMI. To align the work with recent contributions from others, similar models could be tested and compared to those described by Gronum et al. (2016) or Zott and Amit (2007).

Recommendations for the Literature

Some questions lie beyond the possible research areas of ENVISION and will need to be addressed in novel studies. A challenging but rewarding study would be to investigate BMI performance consequences over time in a longitudinal study. It may be costly to obtain an informative data set on BMI that is sufficiently large and includes a temporal dimension. Nevertheless, once established, this would provide opportunities to investigate the complex links between BMI and performance in further depth. As overviewed by others, the lag between BMI and performance may be substantial, and could depend on context (Foss & Saebi, 2017b; Philipson, 2016). It would be interesting to see how activity in BMI phases may differ between flourishing firms and average performing firms, or low performing firms. The dynamics of BMI processes, the possible patterns and cycles could be investigated by use of cross-lagged panel models and could contribute to our understanding of BMI. Future work should therefore concentrate on performance implications of BMI over time.

A different approach may be to relate perceived indicators to real numbers. The study here involves measures using Likert scales rather than information on actual financial numbers. Obviously, the use of actual numbers would make little sense when using a population as heterogenic as presented here. When the data is sampled according to strict rules that narrow down to a niche, the intercompany variance may be reduced to an extent that enables the use of actual financial ratios. Scholars that aim to pursue this direction may want to combine SEM with fsQCA, since fsQCA has the flexibility to suppress the effect of outliers in the process of calibration. Ultimately, this would elucidate whether BMI affects actual financial performance.

From a qualitative perspective, a fair amount of academic work lies in the understanding of factors that drive, influence and result from BMI practices. The discussed findings might serve as starting point for those who aim to find interesting organizations for case studies. Investigations of organization at the single case level may help broaden the understanding of BMI and identify novel concepts that deserve attention in quantitative studies. In interesting approach would be to investigate differences in BMI practices between micro, small and medium sized organizations. Larger studies that rely on multiple case studies could explore the use of fsQCA and convert qualitative differences to binary conditions. This could help to identify combinations of factors that are important for BMI consequences.

Independent of specific research interest, scholars should build on the work of each other and report the used operationalization of BMI in a transparent way. It is a widely held view that this becomes of increasing importance in the coming years since the amount of literature is steeply increasing. If the field is to move forward and adapt to a congruent understanding of BMI, these matters must be followed with severe commitment. There remain numerous interesting gaps for the field; the filling of which can advance the field and can contribute to theory and practice.

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Appendix

Supplementary figures

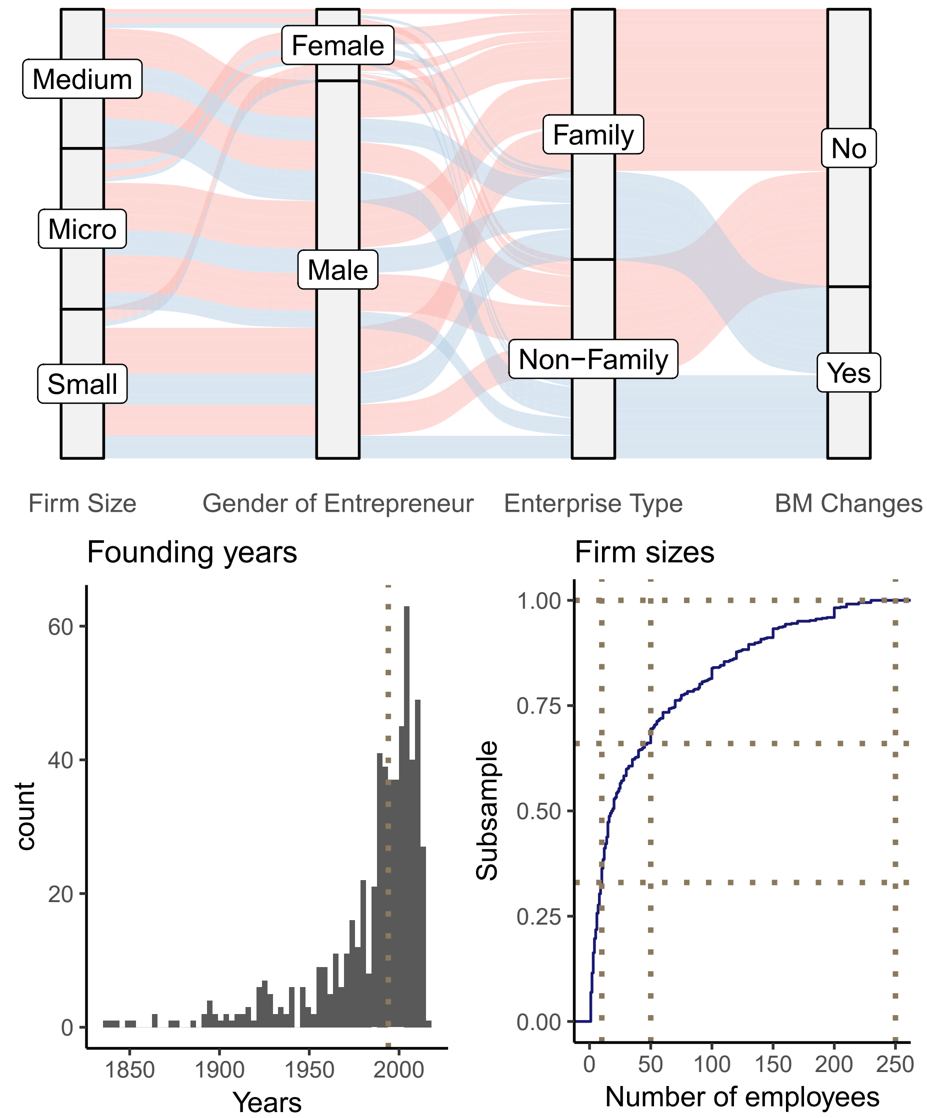

Figure S1. Demographic characteristics of sample.

Top: From the SMEs that were included in the study, 38% recognized the made changes as Business Model Innovation. Relatively, this number was higher in non-family SMEs (42%) compared to family SMEs (35%). The firms with male CEOs more frequently acknowledged these changes as BMI (39%) when compared to firms with female CEOs (31%). Medium sized enterprises reported BM changes more often (43%) compared to small enterprises (40%) and micro sized enterprises (30%).

Bottom left: Distribution of foundation years. From the 584 SMEs being investigated, most firms were founded around the year 2000. The median of the sample appeared to be 1994.

Bottom right: The data was sampled to obtain roughly equal numbers of micro, small and medium sized firms. It appeared that firms, especially smaller ones, tend to locate to the lower bound of the size limit, as can be seen from the non-linear shape of the cumulative density distribution. For example, micro firms with less than five employees were higher represented (60%) when compared to micro firms that contained five or more employees (40%).

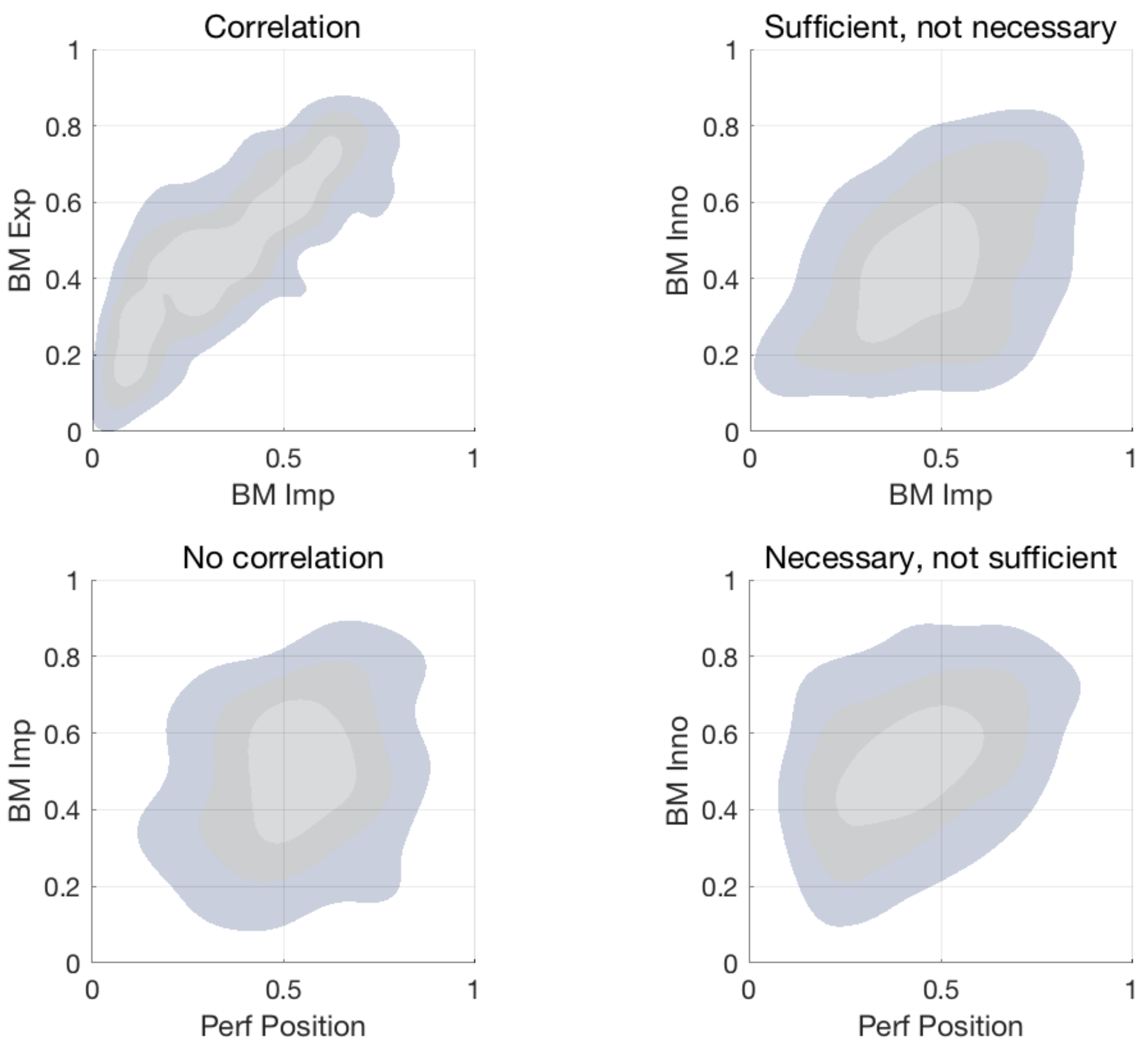

Figure S2. Using Kernel plots to identify asymmetric relations.

Especially when factor scores are based on multi-item constructs (N > 4), Kernel densities can be used to easily identify asymmetric relations. By investigating the shape of the kernel densities, asymmetric relations can be identified and quantified.

Top left represents a typical correlation, where increasing one construct results in increase of the other and vice versa. Top right represents an asymmetric relation, a sufficient but not necessary relation of Y construct (BM inno) on X construct (Perf Position). Increasing Y is sufficient to result in increases of X, but X can also increase without increasing Y. This relation is often found when concepts are related to complex dependent variables that may be affected by many factors. Bottom left demonstrates no correlation, and the kernel density forms a circle. Bottom right shows an asymmetric relation with a necessary, not sufficient relation from construct Y to X. Increasing Y is necessary for an increase in X, but an increase in Y alone may not be sufficient to result in an increase of X.

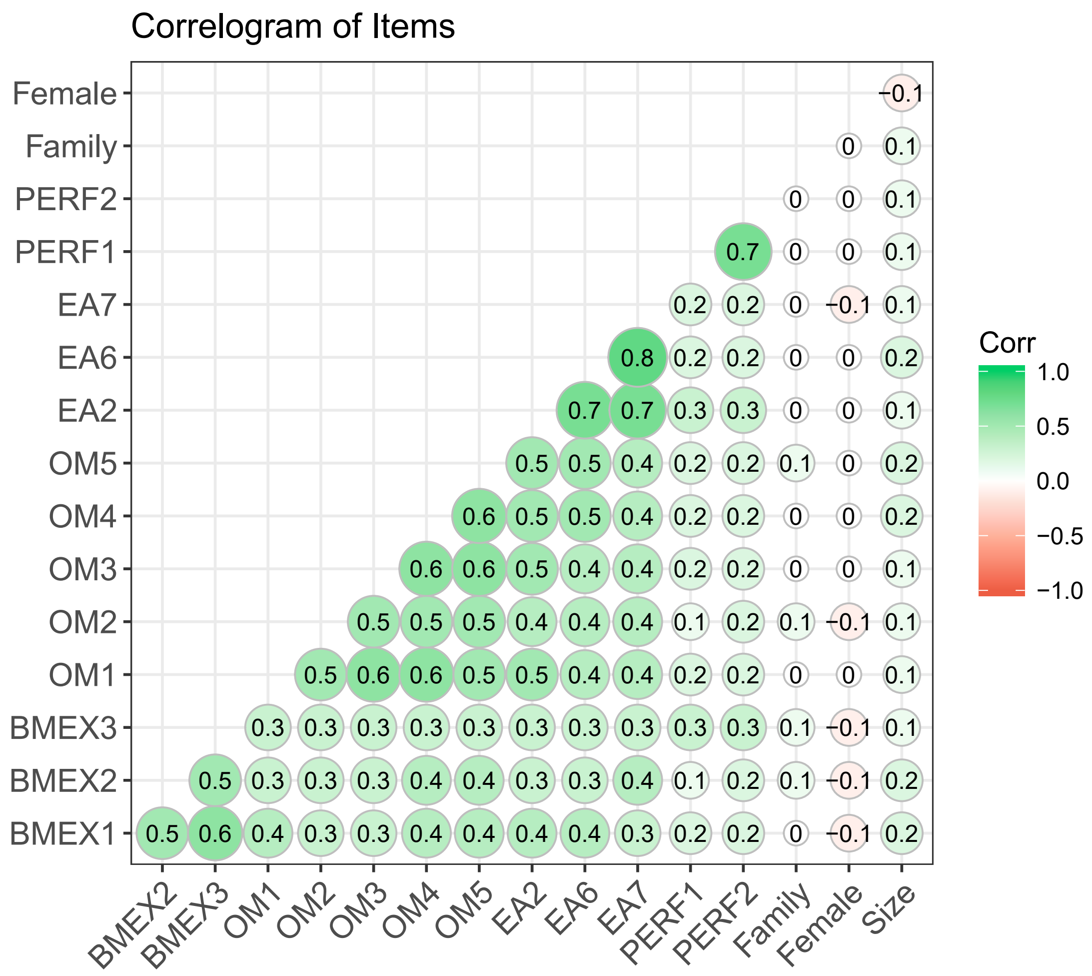

Figure S3. Correlation of items in final measurement model

Correlation of items in measurement model. Most items have some correlation with all the others, but the strength of the correlation coefficient is low (typically 0.1-0.3). Although the coefficient is low, this suggests there may be some common method bias involved in the data. Within the same latent variables, items share more correlation with each other. This matches the EFA results, where factors were found representing the concepts.

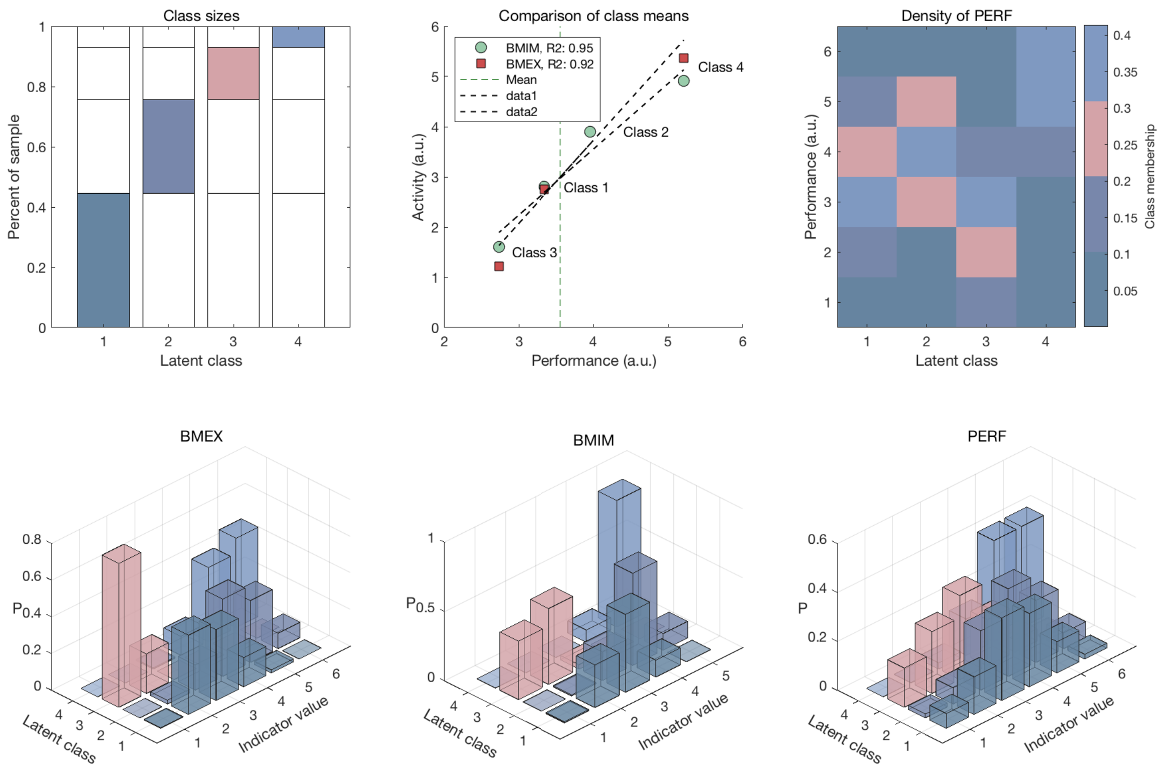

Figure S4. Visualization of cluster profiles

Four latent classes were identified, two big classes (1 and 2) with average profiles around the mean and two smaller classes (3 and 4) with average profiles having more extreme numbers. When plotting the average class means, it becomes clear that BMEX and BMIM have a near linear relation with PERF based on the average numbers for each class. This suggest that, on average, a cluster with more activity in BMEX and BMIM is found to report higher PERF. When looking at the membership scores of PERF, great differences can be observed between class 3 and 4, where class 4 has high representation around the Likert-item score of 6/7, and class 3 has high representation around Likert-item score of 2/3. These differences can well be contrasted by visualizing histograms of the three concepts. Class 4 contrasts with class 3, and these differences are similarly but more mildly found between the bigger classes 1 and 2.

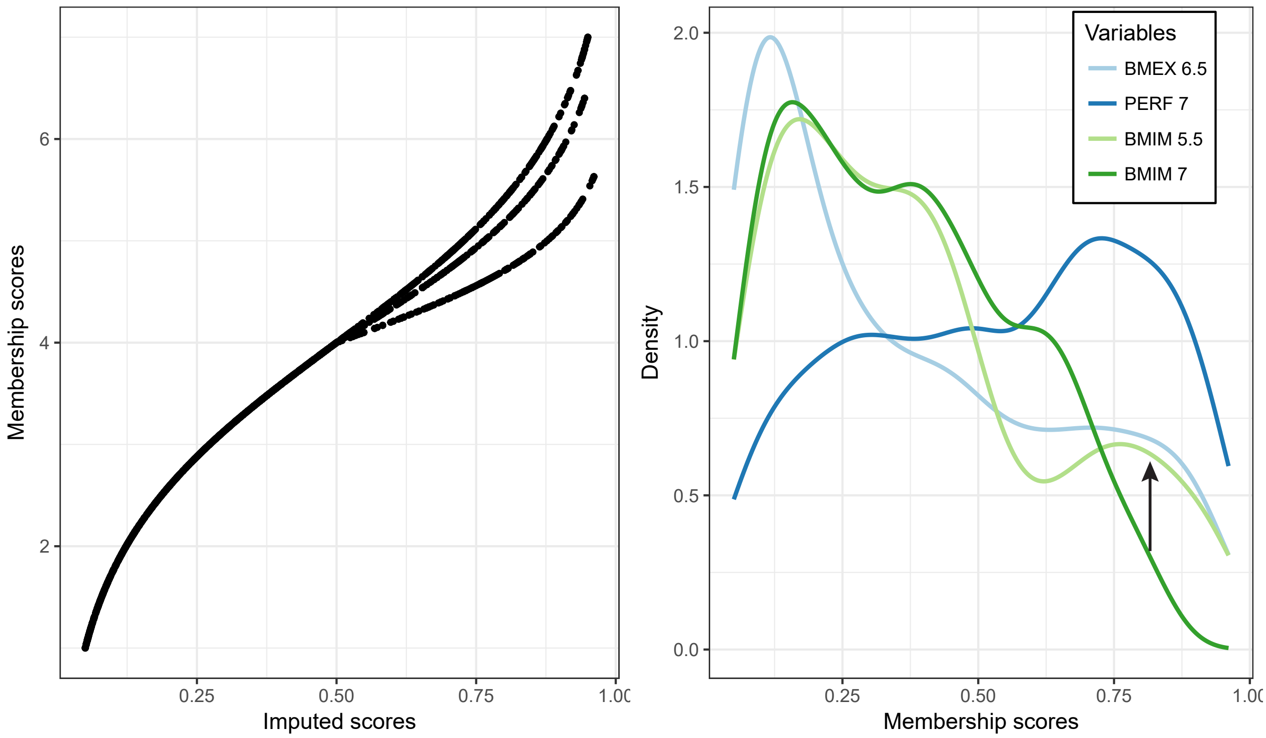

Figure S5. Calibration of fsQCA using S-shaped functions.

Calibration requires manual input of anchor points: lower bound, turning point and upper bound. While lower bound and turning point may be evident, upper bound can differ among constructs, because the maximum score can be dependent on the number of items used for measuring the construct. This is an artefact from linear regression imputation that must be considered while performing fsQCA calibration. BMIM, which was measured with the most indicators (N = 7) has a higher upper bound compared to PERF, which was measured with few (N = 2) indicators. If the upper bound is left the same, BMIM will face severe suppression in it's representation in fuzzy set (dark green line). Adjusting this limit to a lower value requires manual investigation and is needed to maintain a similar distribution shape (light green line). The same, although with less importance, can be said for BMEX (N = 3), where some lower upper bound helps to maintain the distribution shape (blue line).

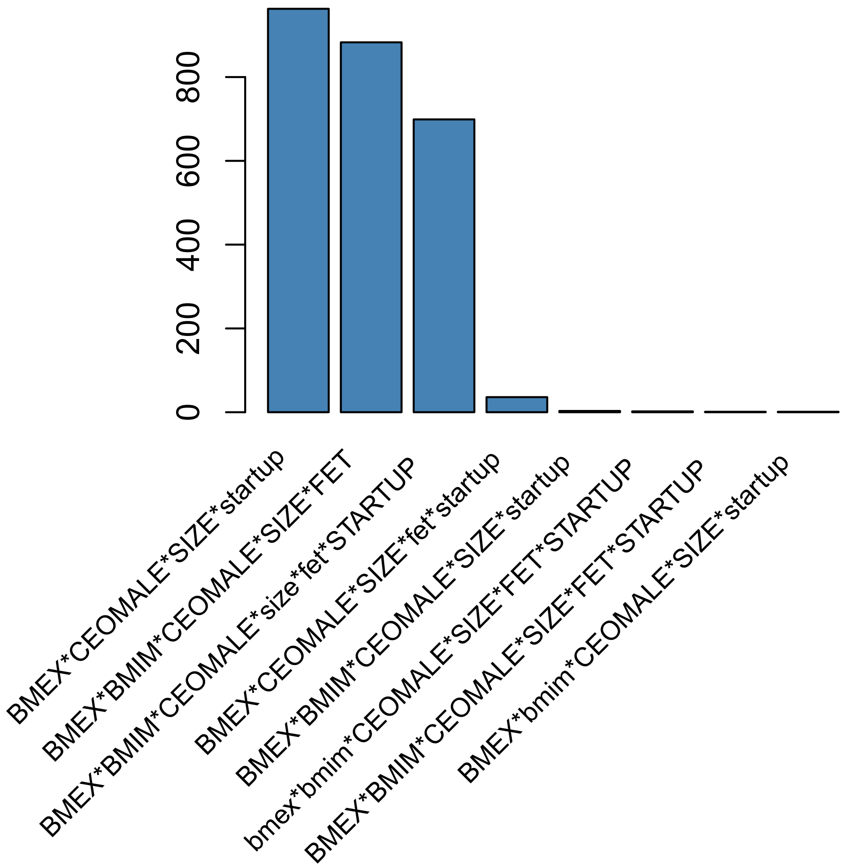

Figure S6. PI Histrogram of fsQCA with 6 conditions

Prime implicants for the Monte Carlo-like simulation using six conditions. Although few additional prime implicants are identified in the histogram, no prime implicant occurs with reasonable frequency other than the first three. This finding supports the robustness of the fsQCA result and indicates that the results are not dominated by a small cluster in the data. Within the three dominant prime implicants, BMEX and BMIM are consistently identified, suggesting that the presence of both forms a good starting point for the prediction of high PERF.

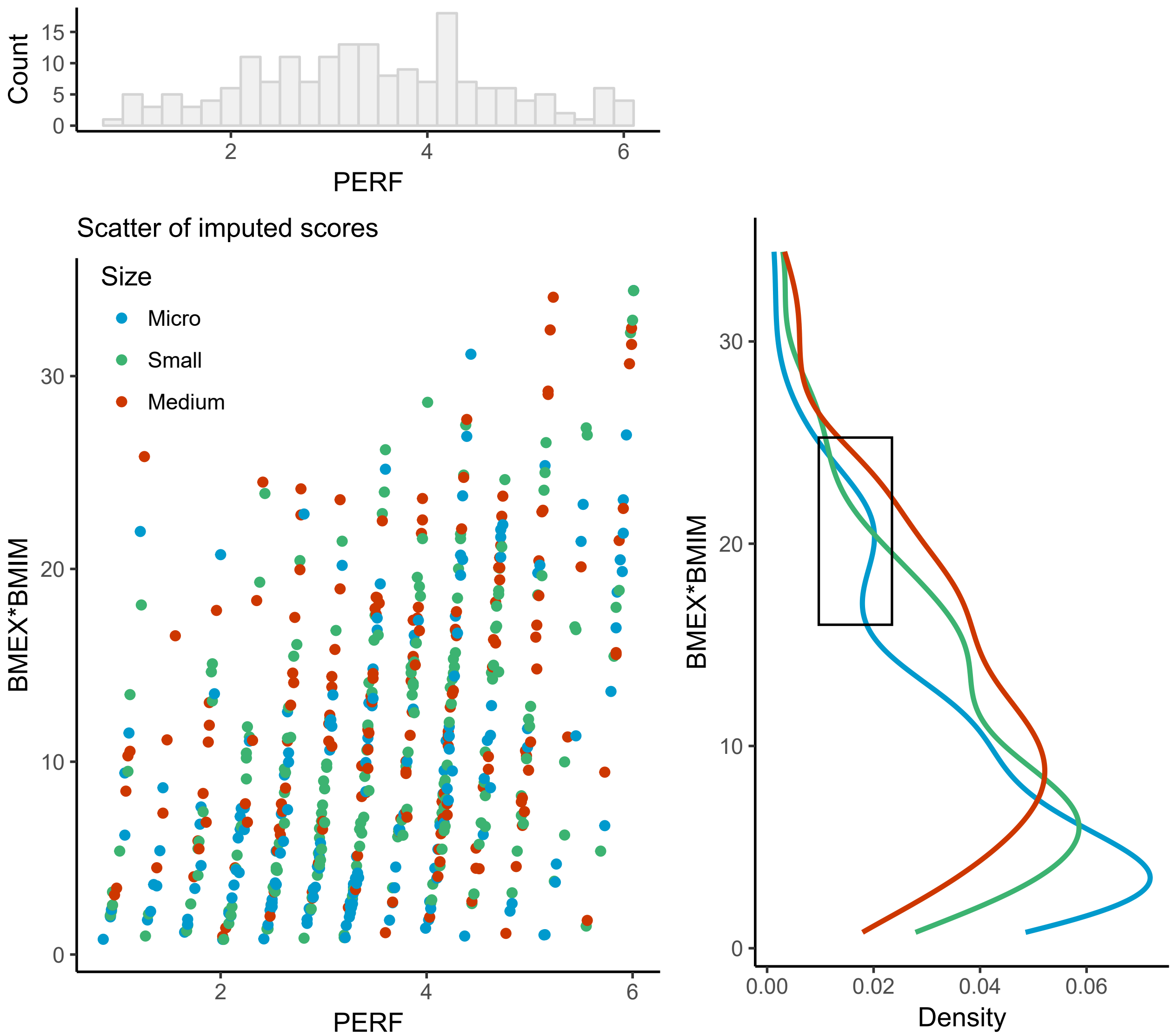

Figure S7. Factor score for size groups.

Because of their correlation, a multiplication of BMEX and BMIM can be used to sort firms based on their BMI engagement. This helps to identify the firms that are engaged in both practices and compare this group among different types of firms. As can be seen from the scatter plot, there is a higher group of micro firms (blue line) that is engaged in both than there is for small firms (green line). This support the finding of the LCA, where representation in the excellent cluster of the micro firms was found to be higher compared to small firms.

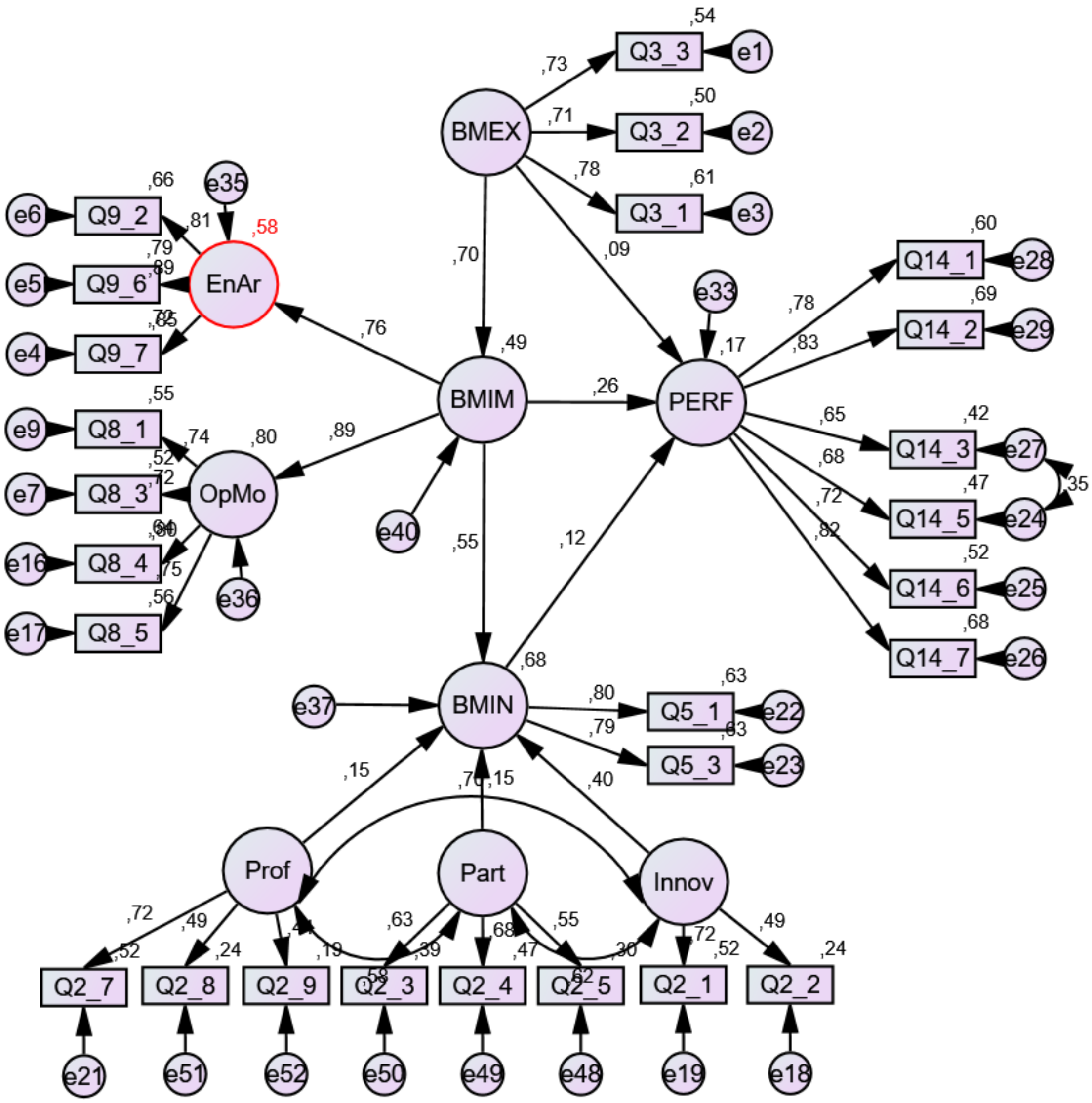

Figure S8. BMI mimic modelling.

As discussed, BMI can be operationalized by a variety of different ways. We have considered the option to extent BMEX and BMIM with an additional, more advanced phase representing completed innovation practices (BMIN). Here, we have followed the idea to model BMIN as MIMIC model, where three separate components represent the definition of Teece (2010) and include innovation in value creation, capture and proposition. This idea, which has been shown more comprehensively by Claus (2017) can be an alternative direction for modeling BMI. However, we found conflicting scales when combined with BMEX and BMIM, which is why we did not investigate this approach in further depth.

Supplements

Supplement A. Envision survey

Introduction

Commissioned by the European Union, The Envision consortium, carries out research on business model innovation. Therefore, we would like to speak to the owner, the core manager or the person within your organization who is responsible for Business Model Innnovation. Your input is important for us to find out how you conduct innovation in your business, and how this contributes to the growth of your enterprise. Eventually, these insights can be shared back to you to improve your enterprise's business performance and innovativeness.

We would appreciate your taking the time to complete the following questionnaire. This questionnaire should take approximately 15 to 20 minutes of your time. Your responses are voluntary and will be confidential. Responses will not be tracked back to individuals. All responses will be compiled together and analyzed as a group.

Thank you for your time

We kindly expect you to submit the questionnaire no later than …….

Instructions

Please choose only one correct answer according to your knowledge, unless specifically instructed otherwise in the question. The answer might be provided either in a form of a 7 point-Likert scale, dichotomous scale (yes or no), or an open answer.

General Instructions:

S0. Are you responsible for Business Model Innovation within your organization?

[ENQ if needed: The core of a company is its business model. Business models describe the core logic of how to deliver value to customers and create revenues.]

Yes

No (ask for correct person)

Screener Question

S1. The core of a company is its business model. Business models describe the core logic of how to deliver value to customers and create revenues. Sometimes, companies change their business model. Did your company make this change during the last 24 months? Yes No Don't know.

For all answers. Next I will give you some examples of Business Model Innovation.

S2a. **For instance, a company no longer wants to sell products but earn money by renting them out, or make money by bundling the product with services.**

Did your company make this type of change during the last 24 months? Yes No

S2b. Or a company enters a new market or starts working with new type of partners.

Did your company make this change during the last 24 months? Yes No

S2c. Another example is changing the pricing strategy, that goes beyond the regular price adaptations.

Did your company make this change during the last 24 months? Yes No

S2d. The last example of a Business Model innovation is the incorporation of IT for business purposes for example using social media or big data IN SALES CHANNELS or IN MARKETING.

Did your company make this change during the last 24 months? Yes No

PROG Instruction: if one of the four questions is answered with yes then the company qualifies for inclusion.

Quota question

Q17b. How many employees does your enterprise have?	open	DK/refused
Q17d. In what industry does your enterprise operate? See Annex	open	DK/refused

PART 0: BUSINESS KNOWLEDGE AND INFORMANT KNOWLEDGE

What is the level of agreement with the following statements?	1 to 7	Source
Q1_1. I understand the product/service offerings of my enterprise		Atuahene gima (2005)
Q1_2 I understand how my enterprise makes money		Atuahene gima (2005)
Q1_3 I am involved in developing new product/services		Atuahene gima (2005)

PART 1 – BUSINESS MODEL

BM Innovation	1 to 7	Source
During last year, our enterprise		
Q2_1. introduced new products		CIS 2008-2010
Q2_2. introduced new services		CIS 2008-2010
Q2_3. started to collaborate with new business partners		Zott & Amit, 2007
Q2_4. Shared new responsibilities with business partners		Itami & Nishino, 2010; Zott & Amit, 2007;
Q2_5. introduced new distribution channels		CIS 2008-2010
Q2_6. Created new revenue streams		Johnson, Christensen, & Kagermann, 2008
Q2_7. Introduced new ways to be profitable		Johnson, Christensen, & Kagermann, 2008
Q2_8. Introduced new pricing mechanisms		Johnson, Christensen, & Kagermann, 2008
Q2_9. Introduced new ways to reduce fixed costs		Lindgardt, Reeves, Stalk, & Deimler, 2009
Q2_10. Introduced new ways to reduce variable costs		Lindgardt, Reeves, Stalk, & Deimler, 2009

BM experimentation	1 to 7	Source
During last year, our enterprise		
Q3_1. Experimented with the (implementation of) their business model		Sosna et al; 2010
Q3_2. Had a specific team to manage business model changes		Sosna et al; 2010
Q3_3. Allocated budgets for business model experimentation		Sosna et al; 2010; Teece, 2010

BM Practices/Processes	1 to 7	Source
Business model is..		
Q4_1. used to gain competitive advantages		Ireland, Covin, & Kuratko, 2009; Ireland et al., 2003
Q4_2 designed in response to market circumstances		Osterwalder, 2004
Q4_3 developed with help of consultants		DaSilva & Trkman, 2013
Q4_4 derived from enterprise's strategy		Osterwalder, 2004

PART 2– BUSINESS MODEL INNOVATION

BMI Architectural	1 to 7	Source
During last year, in our enterprise there were changes		
Q5_1. introducing new components of the business model		Hartmann & Oriani, 2013
Q5_2. In the business model that are new to the world		Cavalcante, Kesting, & Ulhøi, 2011
Q5_3. introducing new ways of combining core components of the business model		De Reuver, Bouwman, & Haaker, 2013; Linder & Cantrell, 2000

BMI Reach	1 to 7	Source
Industry. During last year, the changes in our business model		
Q6_1. Were new to your industry		Christensen & Raynor, 2003; Johnson et al., 2008
Q6_2. Have never been implemented by competitors before		Christensen & Raynor, 2003; Johnson et al., 2008
Q6_3. cannot be found in the dominant business models of your industry		Christensen & Raynor, 2003; Johnson et al., 2008
Market. During last year, the changes in our business model		
Q6_4. focused on a complete new market segment		Chesbrough & Rosenbloom, 2002
Q6_5. Introduced new ways to transact with customers		Zott & Amit, 2007; Wells & Gobeli, 2003
Q6_6. Introduced new ways of organizing relations with customers		Osterwalder & Pigneur, 2005

BM Originality/Radicality	1 to 7	Source
During last year, the changes in our business model		
Q6_7. Were the result of internal proposals		Aspara, Hietanen, & Tikkanen, 2010; Kim & Min, 2015
Q6_8. Were not invented by other enterprises		Aspara, Hietanen, & Tikkanen, 2010; Kim & Min, 2015
Q6_9. Were not adaptations of other existing business models		Aspara, Hietanen, & Tikkanen, 2010; Kim & Min, 2015

PART 3– BUSINESS MODEL ONTOLOGIES / TOOLING

Use of BM Ontologies		Source
Business models can be analyzed by using methods, such as the Canvas model, STOF, etc. Q7. Have you ever used such business model method?	Y/N	Osterwalder, 2004
If yes, please indicate which method:…. Q7A_1. Canvas Q7A_2. LEAN Canvas Q7A_3. Other (OPEN QUESTION, perhaps pre code (1) Canvas and (2) Lean Canvas)	open	Osterwalder, 2004

Use of BM Tooling	1 to 7	Source
To what extent do you use the following tools to support business model innovation:		
Q7B_1. computer based tools		
Q7B_2. paper based tools		
Q7B_3. spreadsheets like Excel		
Q7B_4. board games		
Q7B_5. sticky notes		
Q7B_6. others, namely		

Operating Model	1 to 7	Source
The changes in your business model can have an effect on what your do on a daily basis. To what extent did changes in your business model lead to new ways of…		
Q8_1. standards how you deliver products/services to customers		Ross, Weill, & Robertson, 2006
Q8_2. division of work between your enterprise and external partners		Ross, Weill, & Robertson, 2006
Q8_3. Ways to manage cost to deliver products/services profitable		Lindgardt, Reeves, Stalk, & Deimler, 2009
Q8_4. ways to execute processes		Lindgardt, Reeves, Stalk, & Deimler, 2009
Q8_5. organizational structures		Lindgardt, Reeves, Stalk, & Deimler, 2009
Enterprise Architecture (EA)	1 to 7	Source
The changes in your business model can also have an effect on your ICT. To what extent did changes in your business model lead to changes in your…		
Q9_1. key business processes		Ross, Weill, & Robertson, 2006
Q9_2. Information Technology		Ross, Weill, & Robertson, 2006
Q9_3. internal controls to monitor processes		Op't Land, Proper, Waage, Cloo, & Steghuis, 2009
Q9_4. business processes standardization		Ross, Weill, & Robertson, 2006
Q9_5. business processes integration		Ross, Weill, & Robertson, 2006
Q9_6. ICT applications		Ross, Weill, & Robertson, 2006; Solaimani, 2014
Q9_7. ICT infrastructure		Ross, Weill, & Robertson, 2006; Solaimani, 2014
Q9_8. social media usage		Ross, Weill, & Robertson, 2006; Solaimani, 2014
Q9_9. business/organization structure		Bernus, Nemes, & Schmidt, 2003; Chen, Doumeingts, & Vernadat, 2008; Solaimani, 2014
Q10. To what degree is your main product/service offering enabled by ICT?		

PART 4 – INTERNAL AND EXTERNAL DRIVERS

Innovation activity	1 to 7	Source
In the past 12 months, we changed our business model because we decided to introduce …		
Q11_1. New product development, innovation and R&D activity		CIS 2008-2010
Q11_2. Innovation and/or R&D activities		CIS 2008-2010
Q11_3. Advertising products and services in a new way		CIS 2008-2010

Strategy	1 to 7	Source
In the past 12 months, we changed our business model because we decided to…		
Q11_4. Offering products/services at low prices		Zott and Amit (2008)
Q11_5. Minimize costs		Zott and Amit (2008)
Q11_6. to scale up your business		Zott and Amit (2008)
Q11_7. To focus your product offering		Zott and Amit (2008)

Regulation	1 to 7	Source
In the past 12 months, we changed our business model because of…		
Q12_1. Rapidly changing regulation		Adapted from Jaworski & Kohli, 1993; Teece, 2010

Competitive intensity	1 to 7	Source
In the past 12 months, we changed our business model because of…		
Q12_2. Price competition		Jaworski & Kohli (1993)
Q12_3. Competitors starting to offer similar products/services		Jaworski & Kohli (1993)
Q12_4. Competitor's reactions to your initiatives		Jaworski & Kohli (1993)

Market turbulence	1 to 7	Source
In the past 12 months, we changed our business model because of…		
Q12_5. Frequently changing customer preferences		Jaworski & Kohli (1993)
Q12_6. Customer needs different to traditional customer needs		Jaworski & Kohli (1993)

Technology turbulence	1 to 7	Source
In the past 12 months, we changed our business model because of…		
Q12_7. Rapid changing technology		Jaworski & Kohli (1993) ;de Reuver, Bouwman, & MacInnes, 2009
Q12_8. Rapid increasing technological development		Jaworski & Kohli (1993) ;de Reuver, Bouwman, & MacInnes, 2009

PART 5 – INNOVATIVENESS

Open-Mindedness	1 to 7	Source
Q13_1. Managers encourage employees to "think outside of the box."		Hult, Hurley & Knight, 2004; Calantone, Cavusgil, & Zhao, 2002
Q13_2. Our corporate culture is focused on constant innovation		Hult, Hurley & Knight, 2004; Calantone, Cavusgil, & Zhao, 2002
Q13_3. Original ideas are highly valued		Hult, Hurley & Knight, 2004; Calantone, Cavusgil, & Zhao, 2002

Entrepreneurial orientation	1 to 7	Source
Q13_4. Our enterprise accepts risks		Atuahene-Gima & Ko (2001); Li, Liu, & Zhao (2006); Naman & Slevin (1993)
Q13_5. Our enterprise shows perseverance in turning ideas into reality		Atuahene-Gima & Ko (2001); Li, Liu, & Zhao (2006); Naman & Slevin (1993)
Q13_6. Our enterprise ability to identify new opportunities		Atuahene-Gima & Ko (2001); Li, Liu, & Zhao (2006); Naman & Slevin (1993)

Average number of innovations	1 to 7	Source
Q13_7. Our enterprise aims to create multiple innovations annually		Aspara et al, 2010
Q13_8. Our enterprise introduce innovations that are completely new to the market		Subramanian & Nilakanta, 1996
Q13_9. Creating more than one innovation at the same time is common practice in our enterprise		Subramanian & Nilakanta, 1996

Average Time of Innovation introduction	1 to 7	Source
Q13_10. Our enterprise is one of the first to introduce innovations		Subramanian & Nilakanta, 1996; Rogers, 1983
Q13_11. Our enterprise often waits for some time before introducing innovations		Subramanian & Nilakanta, 1996; Rogers, 1983
Q13_12. Our enterprise only introduces innovations because of others, e.g. customers, suppliers, third parties		Subramanian & Nilakanta, 1996; Rogers, 1983
Q13_13. Our enterprise is often the last one to introduce innovations		Subramanian & Nilakanta, 1996; Rogers, 1983

PART 6 – BUSINESS PERFORMANCE

Overall business performance	1 to 7	Source
What is the level of agreement with the following statements?		
Q14_1. the sales growth of the enterprise		Su,Tsang, & Peng, 2009
Q14_2. the profit growth of the enterprise		Venkatraman & Ramanujam, 1986

Market performance	1 to 7	Source
What is the level of agreement with the following statements?		
Q14_3. Market Share		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996
Q14_4. Speed to market		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996
Q14_5. Penetration Rate		Molina-Castillo & Munuera-Alemán, 2009; Lee & O'Connor, 2003; Golder & Tellis, 1997

Financial performance	1 to 7	Source
What is the level of agreement with the following statements?		
Q14_6. Market Value		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996
Q14_7. Net Income		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996
Q14_8. Return on Investment (ROI)		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996

Customer performance	1 to 7	Source
What is the level of agreement with the following statements?		
Q14_9. Customer Loyalty		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996
Q14_10. Net Profit Margins		Molina-Castillo & Munuera-Alemán, 2009; Griffin & Page, 1996

Q15A. How, approximately, did your enterprise sales develop last year from the previous year? [ENQ: Growth can also be negative. If so please add a minus in front of the percentage. For example -30%]		Aspara et al, 2010
Q15B. How, approximately, did your enterprise profit develop last year from the previous year? [ENQ: Growth can also be negative. If so please add a minus in front of the percentage. For example -30%]		Aspara et al, 2010
Q15C. What is your net profit margin (%)?	open	Brannback, Carsrud, & Kiviluoto, 2014

PART 7 – GENERAL INFORMATION OF THE ENTERPRISE

Overall information		Source
Q16A. awards him/herself salary of	awards him/herself salary of	awards him/herself salary of
Q16B. Cap op value 10 (kEruo a month)	Cap op value 10 (kEruo a month)	Cap op value 10 (kEruo a month)
Q16C. [open box with max of 10] x 1.000 euro's a month	[open box with max of 10] x 1.000 euro's a month	[open box with max of 10] x 1.000 euro's a month

Firm structure		
Q17a. In what year was your enterprise founded?	open	open
Q17c. What is your sales volume?	open	open
Q17e. Please shortly describe your main product/service offering	open	open
Q17f. Is your enterprise part of an enterprise group?	DK/refused	DK/refused
PROG:If the answer to previous question is 'yes', then ask:	open	open
Q17g.In which country is the head office of your group located?	DK/refused	DK/refused
Q17h. Does the Enterprise collaborate with other Enterprises from different industries?	open	open

Q17i. In which geographic markets did your enterprise sell goods and/or services?	DK/refused	DK/refused
Q17j. Do you consider your enterprise to be a family enterprise	Y/N	Y/N
Q17k. Is the enterprise being managed by family members?	DK/refused	DK/refused
Q17l. Percentage shares controlled by family	open	open
Q17m. Percentage of family members present in management team	DK/refused	DK/refused
Q17n. Does the Chief Executive Officer (or the main manager) belong to the family who is controlling the enterprise?	Y/N	Y/N
Q17o. Are females part of the owners/entrepreneurs?	DK/refused	DK/refused
Q17p. Are females involved in strategic decision making process?	open	open
Q17q. Percentage of women in management team	DK/refused	DK/refused

For ENVISION Empowering SME Business Model Innovation – Project

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About ENVISION

In the current tough economic environment, business model innovation can be the key to becoming or staying competitive. To support European competitiveness and job creation, the ENVISION project aims at activating small and medium sized enterprises (SME) across Europe to re-think and transform their business models with the help of an easy-to-use, open-access web platform. Through this platform, every small or medium company, regardless of the country, sector or industry, will be guided in selecting the right tools for their business makeover. The platform is being built for the use of 20 million European SMEs.

The ambitious goal of the ENVISION project is pursued by a consortium of nine partners from seven countries: Delft University of Technology (The Netherlands), University of Turku (Finland), Innovalor Ltd (The Netherlands), evolaris next level Ltd (Austria), University of Maribor (Slovenia), University of Murcia (Spain), AcrossLimits Ltd (Malta), bgator Ltd (Finland), Kaunas University of Technology (Lithuania).

Website:
Facebook:
Twitter: @innovateBM

Supplement B. Approach for visualizing Kernel Densities (MATLAB).

Based on Shimazaki (2010)

```
clear all;
close all;

% Imputed factor scores from AMOS using linear regression
load nPERF_BMEX.txt
x  = nPERF_BMEX;

% Normalize 0 - 1
x(:,1) = (x(:,1) - min(x(:,1)))/(max(x(:,1))-min(x(:,1)));
x(:,2) = (x(:,2) - min(x(:,2)))/(max(x(:,2))-min(x(:,2)));
N_total = length(x(:,1));
W = logspace(-2.2,-.5,50);

% Compute a Cost Function
tau = triu( ones(N_total,1)*x(:,1)' - x(:,1)*ones(1,N_total), 1);
idx = triu( ones(N_total,N_total), 1);
TAU1 = tau(logical(idx)) .^2;
tau = triu( ones(N_total,1)*x(:,2)' - x(:,2)*ones(1,N_total), 1);
TAU2 = tau(logical(idx)) .^2;
TAU = TAU1+TAU2;
C = zeros(1,length(W));
for k = 1: length(W)
    w = W(k);
    C(k) = N_total/w/w + 2/w/w*sum(sum(exp(-TAU/4/w/w) - 4*exp(-TAU/2/w/w) ));
end
C = C/4/pi;

% Selection of Optimal Bandwidth
[optC,nC]=min(C); optW = W(nC)

% Scatter
subplot(2,3,1)
scatter(x(:,1),x(:,2), 8, [0.09 0.18 0.34])
xlabel('PERF');
ylabel('BMEX');
axis square;
title('Scatter','FontWeight', 'normal' , 'FontSize', 12);

subplot(2,3,4);
gn = 80;
x_grid = linspace(0,1,gn);
y_grid = linspace(0,1,gn);
Z = zeros(gn,gn); X = Z; Y = Z;
gauss2d = @(x,w) 1/(2*pi*w*w) * exp(-sum(x.^2,2)/2/w/w);
for i = 1: length(x_grid)
    for j = 1: length(y_grid)
        d = ones(N_total,1)*[x_grid(i) y_grid(j)] - x;
        Z(i,j) = mean( gauss2d(d,optW) );

        X(i,j) = x_grid(i);
        Y(i,j) = y_grid(j);
    end
end

% Surf
surf(X,Y,Z);
shading interp;
mycolors = [1 1 1; 0.47 0.53 0.67; 0.50 0.52 0.53; 0.50 0.52 0.53; 0.63 0.64 0.66;
0.63 0.64 0.66; 0.63 0.64 0.66; 0.63 0.64 0.66; 0.63 0.64 0.66; 0.63 0.64 0.66;  0.63
0.64 0.66; 0.63 0.64 0.66];
colormap(mycolors);
xlabel('PERF'); ylabel('BMEX'); axis square;
title('Sufficient, not necessary','FontWeight', 'normal' ,'FontSize', 12)
set(gca,'CameraTarget',[0.5 0.5 0]); set(gca,'CameraPosition',[.5 .5 100]);alpha(0.4)
```

Supplement C. Approach for a direct linear calibration (R)

```r
# Direct Piecewise Linear Calibration (adjusted from Liu,
Mezei, Kostakos, & Li, 2017)
library(readxl)
fsData <- read_excel("inputfsQCA_25jan.xlsx")
# Removing rows with unknown answers
ind <- which(with( fsData, FEMALE < 3) & with( fsData, Age >
0))
deleted = nrow(fsData) - length(ind)
fsData <-  fsData[ ind, ]
# Crisp calibration
Dichot <- fsData[,c("FEMALE","Age", "Micro")]
Dichot[is.na(Dichot)] <- 0
bin <- function(x) x-1
Dichot[,c("FEMALE","Age")] <- bin(Dichot[,c("FEMALE","Age")])
Imp_Norm <- fsData[,c("BMEXn","BMIMn", "PERFn")]
# Correction for regression imputation as compared to taking
average
Imp <- fsData[,c("BMEX","BMIM", "PERF")]
Corr <- c(1-min(fsData[["BMEX"]]), 1-min(fsData[["BMIM"]]), 1-
min(fsData[["PERF"]]))
Imp_Corr.1 <- Imp[[1]] + Corr[1]
Imp_Corr.2 <- Imp[[2]] + Corr[2]
Imp_Corr.3 <- Imp[[3]] + Corr[3]
bas <- function(x,a,b,m,n) m+(n-m)*((x-a)/(b-a))
likert <- function(x,m_1,m_2,m_3,m_4,m_5,m_6,m_7)
  ifelse(x < 2, bas(x,1,2,m_1,m_2),
    ifelse(x >= 2 & x < 3,bas(x,2,3,m_2,m_3),
      ifelse(x >= 3 & x < 4,bas(x,3,4,m_3,m_4),
        ifelse(x >= 5 & x < 6,bas(x,4,5,m_5,m_6),
          ifelse(x >= 6 & x < 7,bas(x,6,7,m_6,m_7),0)))))
count <- 0;
Direct.list <- list();
# Anchor points for the membership function
for (n_4 in c(0.5, 0.45, 0.4, 0.35, 0.3, 0.25, 0.2)){
  count <- count + 1
  n_1 <- 0.0
  n_7 <- 1.0
  n_2 <- (n_4-n_1)/3*1+n_1
  n_3 <- (n_4-n_1)/3*2+n_1
  n_5 <- (n_7-n_4)/3*1+n_4
  n_6 <- (n_7-n_4)/3*2+n_4
  Var.cal.1 <- likert(Imp_Corr.1,n_1,n_2,n_3,n_4,n_5,n_6,n_7)
  Var.cal.2 <- likert(Imp_Corr.2,n_1,n_2,n_3,n_4,n_5,n_6,n_7)
  Var.cal.3 <- likert(Imp_Corr.3,n_1,n_2,n_3,n_4,n_5,n_6,n_7)
  Var.cal <- cbind(Var.cal.1, Var.cal.2, Var.cal.3)
  Direct.list[[count]] <- Var.cal
}
```

Supplement D. Computation of Explained Variance

To give insight on how the explained variance is computed, it might help to look at the formula that underlie these operations. Linear regressions are used to fit a line that minimizes the residual errors of the data points, in the case of the plot this means the regression plane seeks the direction that has the lowest combined distance of all the data points to the plane. An independent variable (BMEX) can be linked to the dependent variable (PERF) as presented in the Equation 1. This regression model assumes the relationship between the dependent variable and the regressors to be linear, with the addition of an error variable to add noise to this relationship. This equation can be stacked together and is often presented in vector form as in Equation 2. Regressions models pursue the idea to minimize the sum of squared residuals, the differences between the predicted and real value of the dependent variable, which is commonly referred to as the least-squares approach (Equation 3).

$$y_i = \beta_0 1 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i = x_i^T \beta + \epsilon_i, \quad i = 1, ..., n, \tag{1}$$

$$Y = \alpha + X\beta + \epsilon \tag{2}$$

$$\hat{\epsilon_i} = y_i - \alpha - \beta x_i \tag{3}$$

Residuals are computed subtracting the candidate parameter values in points of the independent variable (e.g. BMEX) from the dependent variable (e.g. PERF). A solution to the model consists of values for a and b that minimize the squared residuals, as shown in Equation 4 and Equation 5. This equation can be solved by equating the derivative to zero which yields solutions as given by Equation 6 and Equation 7. Substituting these values into the formula of a straight-line results in Equation 8, which indicates the role of rxy, the sample correlation coefficient, in the regression line of standardized data points.

$$\min_{\alpha,\beta} Q(\alpha, \beta) = \sum_{i=1}^{n} \hat{\epsilon}_i^2 = \sum_{i=1}^{n} (y_i - \alpha - \beta x_i)^2 \tag{4}$$

$$\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x}, \tag{5}$$

$$\begin{aligned} \hat{\beta} &= \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \\ &= \frac{Cov(x, y)}{Var(x)} \\ &= r_{xy}\frac{s_y}{s_x} \end{aligned} \tag{6}$$

$$\frac{y - \bar{y}}{s_y} = r_{xy}\frac{x - \bar{x}}{s_x} \tag{7}$$

$$\begin{aligned} R^2 &= \frac{SS_{reg}}{SS_{tot}} \\ &= \sum_i (f_i - \bar{y})^2 / \sum_i (y_i - \bar{y})^2 \\ &= 1 - \sum_i \epsilon_i^2 / \sum_i (y_i - \bar{y})^2 \end{aligned} \tag{8}$$

To evaluate the model fit, the coefficient of determination (R-squared) is widely used as way to present the total variance explained. For a model with a single independent variable, the R-squared is equal to rxy2. More complex models require some additional computations, but this approach can be understood by the following set of equations. The explained variance can be considered as the part of the sum of squared regression distances, i.e. model fit to the sample average, from the total variance, i.e. from the actual values to the sample mean. This equals the negation of sum of squared residuals (Equation 8), which are identified during the minimization problem. Ideally, the regression line has minimal residuals, and this yields an R-squared close to one.

Latent Class Models can be used to classify data based on analysis with Bayesian probability theorem (Magidson & Vermunt, 2004). In a general way, a latent class model can be written as in equation, where T denotes the number of latent classes and N the number of manifest variables. Here, N equals three, which can be inserted to obtain Equation 9.

$$\begin{aligned} \pi_{i_1,i_2,\ldots,i_n} &\approx \sum_t^T \pi_t \prod_n^N \pi_{i_n,t}^n \\ \pi_{ijkt} &\approx \pi_t^X \pi_{it}^{A|X} \pi_{jt}^{B|X} \pi_{kt}^{C|X} \end{aligned} \tag{9}$$

The first probability, πtX denotes the probability of being in latent class t = 1, 2, …, T, of latent variable X. The remaining terms indicate the conditional probabilities of obtaining the ith, jth, and kth response to item A, B and C respectively, i.e. BMEX, BMIM and PERF. Subsequently, the aim of the latent class model is to identify the minimum number of classes that is needed to explain away the relationships observed among the manifest variables. This is an iterative process during which the adequate goodness of fit is evaluated by the L2, the likelihood ratio chi-squared statistic, and the Bayesian information criterion (BIC) statistic, which compensates for the sample size and number of parameters.

Next, when model fit is validated, the results of the model are used to classify cases into the appropriate latent classes by comparing the estimates of the posterior membership probabilities and assigning cases to the classes for which this score is the highest. Finally, the R-squared statistic, could again be used as indication of explained variance although it has been said that this could not always me similarly interpreted as in regression models. With an increasing number of manifest variables, the R-square tend to decrease of LC models and sometimes other statistics are preferred for the assessment of model fit, including the pseudo R-squared statistics, such as entropy R-squared, which denotes how well one can predict class membership based on the observed variables.

After calibration, the QCA analysis continues by the establishment of a truth table that consists of 2n rows, with n being the number of different conditions. The truth table list all possible combinations of conditions and the outcome associated to each combination. In addition, it shows which configurations are common and which do rarely happen in the data. Truth table should be solved by establishing cut-offs for causal sufficiency and frequency. This is computed by comparing the membership score of the causal combination with the outcome. For example, in our case, when considering only BMEX and BMIM as conditions to the outcome PERF, the truth table would be solved by comparing multiplied membership scores of BMEX and BMIM to those of PERF. When the multiplied score is always lower than the outcome, it would imply that the causal combination denotes a perfect subset relationship. In contrast, coverage applies the proportion of the sum of membership scores in an outcome that can be explained by the causal combination (Equation 10). A high coverage suggest that the configuration is consistent with the outcome and involves many cases with outcome values that are in the fuzzy set. In a way coverage is the QCA representation of explained variance, yet scholars should be aware of the fundamental differences on how these statistics are computed.

$$\begin{aligned} Consistency(X_i \leq Y_i) &= \sum \frac{\min(X_i, Y_i)}{\sum X_i} \\ Coverage(X_i \geq Y_i) &= \sum \frac{\min(X_i, Y_i)}{\sum Y_i} \end{aligned} \tag{10}$$

Supplement E. LCA configuration and multi-group

To align the covariate outcomes with the output of the fsQCA, three covariates that showed differences (size, CEO gender, family) were added simultaneously and investigated in cross-tabulation. The probability means of the causal combinations were multiplied with the average PERF scores for each of the clusters to obtain a ranking score for each of the configurations. Sorting the combinations based on these scores resulted in a list sorted from poor to high performing combinations of covariates (Table S1, top). It appeared that size was dominant among the three covariates since the list followed order based on firm size. Hereafter, CEO gender appeared to have more impact than classification based on family/non-family. The latter covariate did not cause considerable differences among the subgroups when added as third covariate. Granted that this effect is measured while controlled for two other covariates, it does not mean that the covariate itself does not result in changes, but the changes it causes can be mostly explained by the changes causes by the two others. These finding suggest that from the covariates added, size was the most prevalent in its implications to outcome and might thus be most interesting for further investigation.

Configuration			**Cluster**				**Score**
Full sample			1	2	3	4	3.54
Micro	Female	Non Fam	0.34	0.25	0.34	0.07	3.40
Micro	Female	Family	0.46	0.14	0.29	0.10	3.44
Micro	Male	Non Fam	0.33	0.30	0.29	0.08	3.48
Micro	Male	Family	0.45	0.17	0.26	0.12	3.51
Small	Female	Non Fam	0.38	0.36	0.18	0.08	3.59
Small	Female	Family	0.52	0.20	0.15	0.12	3.59
Small	Male	Non Fam	0.35	0.42	0.15	0.09	3.66
Small	Male	Family	0.49	0.24	0.13	0.14	3.66
Medium	Female	Family	0.53	0.27	0.07	0.13	3.69
Medium	Female	Non Fam	0.38	0.46	0.08	0.08	3.71
Medium	Male	Family	0.49	0.31	0.06	0.14	3.75
Medium	Male	Non Fam	0.33	0.51	0.06	0.09	3.77

		Cluster 1	**Cluster 2**	**Cluster 3**
Micro	Clustersize	0.43	0.29	0.28
Profile	PERF Mean	3.08	4.43	2.72
Small	Clustersize	0.49	0.37	0.14
Profile	PERF Mean	3.52	4.06	2.85
Medium	Clustersize	0.56	0.31	0.13
Profile	PERF Mean	3.46	4.49	2.75

Table S1. Ranking firm characteristics in LCA (top) and multi-group analysis based on Size (bottom).

Finally, we proceed to compare the different firm sizes as separate groups (Table S1, bottom). Deviating from the previous results, the profiles for each of the group had optimal BIC scores when modelled with three latent classes. Notably, the R-squared for the dependent variable (PERF) was considerably different for the different subgroups, with values of 32%, 12% and 22% for the micro, small and medium sized firms respectively.

Among the groups, a similar pattern exists regarding the respective performance of the latent classes. Class 2 consists of the top performing firms with the highest performance. Class 1 represents the densest cluster with in-between performance, and Class 3 contains the firms with poorest performance. Obviously, the cluster sizes as well as the probability means for the latent variables might differ considerable among groups (Table S1). The group with micro firms has a higher cluster size for class 3 (0.28) compared to the group with small (0.14) or medium sized firms (0.13). Since the average performance scores for this class are in comparable range, this indicates that the population of micro firms consists of a higher part of poor performing firms. Now when we consider the high performing class 2, the highest density can be found in the group of small firms (0.37), which is considerably more than the group of micro firms (0.29) or medium firms (0.31). In this case the average performance scores do differ among groups, with medium firms representing the highest average performance (4.49), followed by the cluster of micro firms (4.43) which in turn outcompete the average score of the small firms (4.06). Thus, small firms were found to have the highest proportion of firms in the top performing class, but this class was identified with lower average performance when compared to small and medium sized firms. This finding is consistent with the prior discussed four latent class model, where small firms were found to have a higher average performance but lower representation in the top performing class.

To reveal these differences for the three latent variables, a bubble plot might be used to indicate relations between the average latent variables (PERF vs BMIM and BMEX) with cluster size represented by the size of the points (Figure S9, left). Like the model with four latent classes, a clear relation can be observed between the average activity in BMEX and BMIM with the average PERF score for the different latent classes.

For each of the subgroups, we added the firm characteristics CEO gender, family and age as covariates to study the difference among groups (Figure S9, right). Probability means of the micro firms are in the bottom of the figure, small in the middle and medium on the top. Similar to the results described above, the blue bars representing the low performance cluster are longer in the micro group when compared to the other groups. Likewise, the bars indicating high-performance groups are most represented in the small group, followed by the medium and then micro group. In addition, this visualisation enables comparison of subsamples between the different size groups.

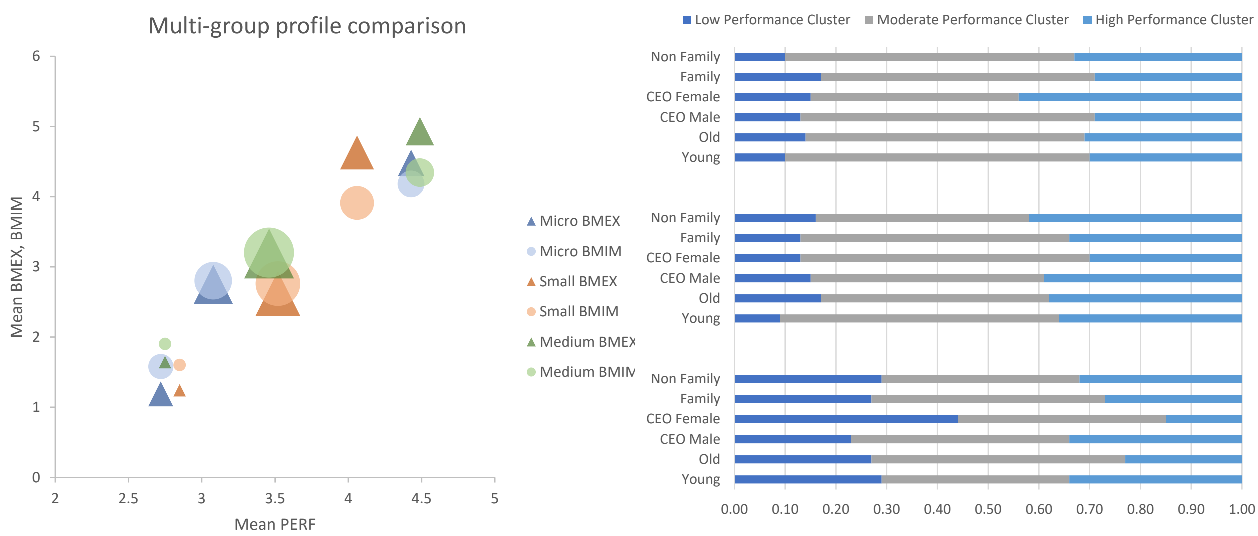

Figure S9. Left: Bubble plot of cluster means. Right: Bar plot of membership scores for each of the three classes.

As can be seen from the Figure S9 (right), within the micro group, firms with female CEOs are underrepresented in the high performing cluster, while they are overrepresented in the low performance cluster. Surprisingly, in the medium group, firms with female CEOs have the highest representation in the high performing cluster. In the small and medium groups, the young firms are characterized by their low representation in the low performance group. Non-family firms, when compared to family firms, tend to slightly outperform in the medium group, while in the micro and small group, the non-family firms have lower presentation in the middle group. This seems to suggest that family firms might pursue a less risky innovation strategy, which results in a higher domination of the average latent class compared to the non-family firms, which have relative more dominance in the low and high classes.

Supplement F. Approach for fsQCA robustness test (R)

```
# Monte Carlo-like, random deletion simulations (based on Emmenegger et
al., 2014)
PI <- c()
counter <- 0
for (i in 1:999) {
  I <- sample(1:nrow(data), round(nrow(data) / 10 * 9))
  MC <- data[I,]
  tt <-
    truthTable(
      MC,
      outcome = "PERF",
      conditions = "BMEX, BMIM, SIZE, MALE, FET",
      incl.cut = 0.85,
      n.cut = 10,
      comle = TRUE,
      use.letters = FALSE,
      show.cases = FALSE,
      dcc = FALSE
    )
  ptt <- minimize(tt, details = TRUE)
  pims <- ptt$pims
  print(colnames(pims))
  c <- length(t(colnames(pims)))
  for (j in 1:c) {
    PI[counter + j] <- colnames(pims)[j]
  }
  counter <- counter + c
}
par(mar = c(7, 4, 2, 2) + 0.4)
P <- table(PI)
P <- sort(P, decreasing = TRUE)


mp <- barplot(P,ylab = "Frequency" ,main = "Histogram of Prime
Implicants", las = 2,
        cex.names = 0.8, cex.lab = 0.9, cex.axis = 0.9,  cex.main = 0.9,
col = "lightgoldenrodyellow",
        axes = FALSE, axisnames = FALSE)
par(mgp = c(2.5, 1, 0))
text(mp, par("usr")[3], labels = rownames(P), srt = 45, adj = c(1.1,1.1),
xpd = TRUE, cex=.7)
axis(2)
```