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Pathways to digital business models: The connection of sensing and seizing in business model innovation

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ABSTRACT

Digital business model innovation (BMI) is critical to achieving and sustaining competitiveness in technology-driven environments. In those environments, firms must not only sense changes to identify opportunities but also effectively seize them in BMI. Therefore, sensing and seizing cannot be considered as isolated dynamic capabilities, but must be combined for successful BMI. However, research on sensing and seizing does not offer compelling suggestions for firms that struggle with connecting both while pursuing digital BMI. We use qualitative configurational analysis (QCA) to analyze a sample of 49 case studies on digital BMI to identify the antecedents that firms sense before seizing these changes with digital BMI. Based on ten configurations of sensing (represented by six antecedents) and seizing (represented by four BMI types), we explain the relationship between sensed antecedents and seized digital BMI. In addition, we derived four variables that explain "what" and "how" firms connect sensing and seizing. Based on the sensing-seizing connection, we introduce consolidating BMI as a new type of BMI unique to the digital context. This novel type enables firms to exploit and explore new BMs and subsequent digital BMIs through the means of digital infrastructure. This study extends the understanding of how different business models emerge and how firms create digital BMIs.

Introduction

The pervasiveness of digital technology enables digital business model innovations (BMIs) at an unmatched pace as well as creates dynamic and complex business environments (Benbya et al., 2020; Tanriverdi et al., 2010). Digital BMIs are essential to coping with these changes and profiting from emerging digital technologies (Teece, 2018b). Firms depend on dynamic capabilities to adapt their business models (BMs) to thrive during the advent of technological change (Lucas and Goh, 2009). Dynamic capabilities describe the proficiencies needed to sense and seize change by forming a coherent BM and transforming resources to achieve a competitive advantage (Teece, 2018a). However, sensing the necessity or opportunity and having the ability to seize that change does not reveal how to seize what is sensed (Tallon et al., 2019). Hence, neither sensing nor seizing is sufficient, and it is critical to connect both (Ravichandran, 2018; Tallon et al., 2019).

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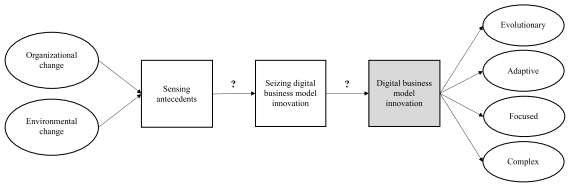

Fig. 1. Research outline.

Firms still struggle to implement digital technology into their BMs and often seize the sensed changes differently (Teece, 2010). For example, the customer demand for grocery delivery reveals how different antecedents lead to different digital BMIs. As part of Amazon's business strategy, AmazonFresh requires an AmazonPrime subscription. Walmart needed a time- and cost-efficient delivery network and therefore uses a digital platform to hire delivery drivers on a transaction basis. In contrast, Trader Joe's or Aldi do not offer any delivery or curbside pick-up services as their customers do not demand such a service. These firms seize digital BMI opportunities differently because of their organizational context, such as their possessed resources. Other possible antecedents of BMI, such as strategy alignment and technological availability, capability, (limited) financial resources, or legal frameworks, further increase the challenge of connecting sensing and seizing (van Oosterhout et al., 2006). These examples illustrate the challenge of translating what is sensed into seizing with digital BMI.

Although research acknowledges the importance of BMI in today's dynamic and digital environment (Doz and Kosonen, 2010), it lacks a thorough explanation of how sensing change and seizing BMIs are connected, as illustrated in Fig. 1 (Foss and Saebi, 2018; Ravichandran, 2018; Saebi, 2015; Tallon et al., 2019). Firms lack guidance and available pathways for BMI to effectively leverage limited resources and capabilities given their current situation and sensing changes (Chesbrough, 2007). It remains unclear why firms undergo digital BMI and what antecedents account for differences in how firms innovate their BMs (Foss and Saebi, 2017, 2018; Saebi, 2015). To explain how firms translate the sensed changes into BM innovations, we tackle the following research question: *What is the connection between sensed antecedents and seized digital BMI?*

We connect sensing and seizing for digital BMI following a qualitative configurational approach. We conduct a case survey of 49 case studies on digital BMIs and use qualitative comparative analysis (QCA) to seek configurational pathways from antecedents to digital BMI. Thus, we review the literature on BMI, the role of dynamic capabilities for BMI, and Foss and Saebi's (2017) BMI typology that informed our coding scheme. In our research approach, we first collected 49 case studies from extant literature and, using open coding, identified six antecedents that firms sensed before seizing digital BMI. Next, we coded the case data using these antecedents and the four BMI types before analyzing the data set with crisp-set QCA (csQCA). The csQCA results in ten configurations of antecedents, leading to four different types of digital BMI. We further analyze these configurations using illustrative examples from our sample. Based on the results, the raw case data, and extant literature on dynamic capabilities and BMIs, we introduce four variables that describe the connection of sensing and seizing: context, attentionality, resources, and orientation.

These four variables explain what and how firms sensed the antecedents and seized the digital BMI. In addition, the variables allow us to connect sensing and seizing to explain how firms create different types of digital BMI. In the discussion, we extend the BMI typology by Foss and Saebi (2017) with how the different types are created and find a new type of BMI unique to the digital context. This novel type enables firms to exploit and explore new BMs and subsequent digital BMIs through digital infrastructure. We discuss how firms leverage dynamic capabilities for digital BMI and the role of this new BMI type. Finally, we conclude the paper with our contributions to research and practice and provide avenues for future research.

Business model innovation and dynamic capabilities

Business model innovations

We use BM as the unit of analysis to elaborate on how firms connect sensing and seizing capabilities to create and capture value in dynamic environments (Teece, 2010). The BM has emerged as a core construct to explain how a firm's strategy and business processes interact (Al-Debei and Avison, 2010). It consists of three interconnected pillars: value creation, value capture, and value delivery (Massa et al., 2017). Each pillar represents sub-systems comprised of multiple, single interdependent activities (Foss and Saebi, 2017). Thus, the BM composes a system of activities that go beyond the focal firm but facilitate interactions with partners and customers (Teece, 2010; Zott and Amit, 2010). This activity system perspective presents a helpful construct to manage environmental dynamism in business strategies (Lanzolla and Markides, 2021). As firms can achieve strategic goals in several ways, numerous BMs can serve the same generic business strategy. The strategy's goal is to find BMs that fit the organizational and environmental context. Lanzolla and Markides (2021) describe the process as "the business model construct – because of its granularity and its focus on bridging value

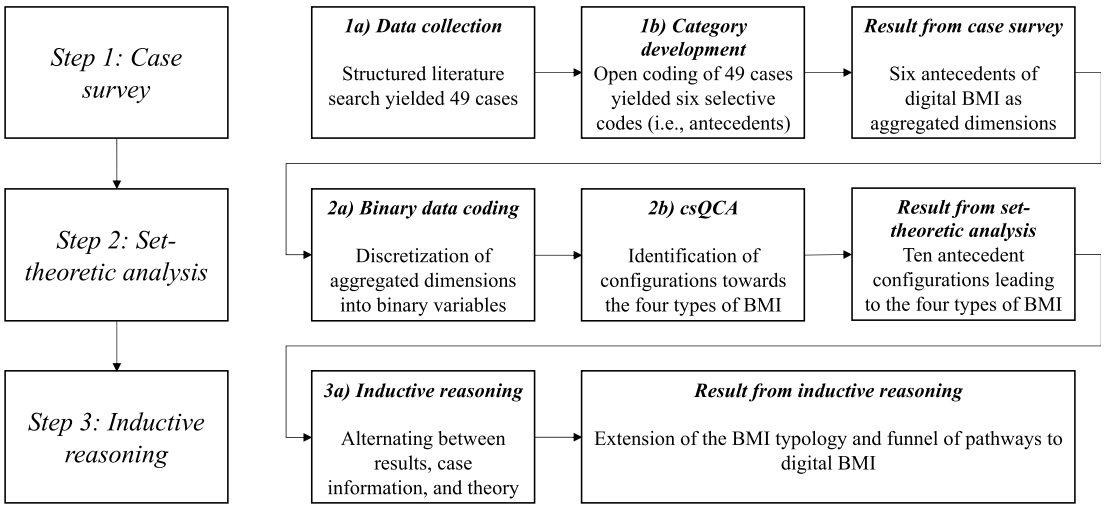

Fig. 2. Research methodology.

creation and value capturing activities – can provide a […] platform to […] develop a less descriptive and more dynamic set of ideas on how to design a superior system of interconnected activities, all else being equal.".

Firms with stronger dynamic capabilities can adapt their BMs in dynamic and digital environments. A firm's ability to perform and profit from BMIs by seizing arising opportunities or avoiding threats articulates its dynamic capabilities (Rai and Tang, 2014; Yeow et al., 2018). Firms with stronger dynamic capabilities are more likely to be balanced between continuing an existing BM while trying to profit from change with an adapted or new BM (Andriopoulos and Lewis, 2010; Weber and Tarba, 2014). Consequently, despite the known performance benefits of BMI (Han et al., 1998; Massa et al., 2017; Van de Ven, 1986), firms struggle to change their BM (Teece, 2010), as they also struggle to build dynamic capabilities. Therefore, BMI is a suitable lens for analyzing how firms connect sensing and seize changes to create and capture value (Steininger et al., 2022; Teece, 2018a; Vial, 2019).

Business model innovation types

BMI is defined as "designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements" (Foss and Saebi, 2017). This definition implies that BMI requires changing fundamental business logic, roles, and responsibilities (Sawhney et al., 2006; Veit et al., 2014). Focusing our research on a digital context, a BMI is digital if the introduction of digital technology, such as a digital platform, significantly innovates the firm's BM, leading to a new IT-related configuration or shift in the BM (Steininger, 2019; Veit et al., 2014).

Foss and Saebi (2017) developed a typology to classify different forms of BMI using the axes of novelty and scope. The typology classifies the degree of novelty of innovation as new to the firm or new to the industry. When it comes to the BMI's scope, the BM can be decomposed in several ways: into multiple interdependent sub-systems (e.g., value creation, value delivery, value capture), into a single sub-system (e.g., a new payment model represented as modular innovation), and into an architectural innovation that changes multiples of such sub-systems and their interdependencies.

Based on the above classification, Foss and Saebi (2017) identify-four types of BMI: evolutionary, adaptive, focused, and complex. Seizing change through BMI can take all four forms. Evolutionary and adaptive innovations are not new to the industry but new to the firm. Whereas evolutionary BMI refers to fine-tuning individual BM sub-systems, adaptive BMIs represent changes to the whole BM. A focused innovation implies a change in individual BM sub-systems that are also new to the industry. Last, complex BMI describes the adjustment of the entire BM of a firm that is also new to the industry.

Theoretical research outline

The extant literature on dynamic capabilities indicates that the connection between sensing and seizing is still unclear (Schilke et al., 2018) (see Fig. 1), which also hinders the design of repeatable mechanisms in digital BMIs (Vial, 2019). Foss and Saebi (2017) point to the current challenge in both BM research and practice to illuminate the process from conjecture to implementation of a specific digital BMI to seize a sensed need. We use the four types of BMI to classify the seized digital BMIs and link them to configurations of sensed antecedents.

Research method

To analyze the connection of sensing and seizing capabilities, we followed a three-step process combining a case survey with

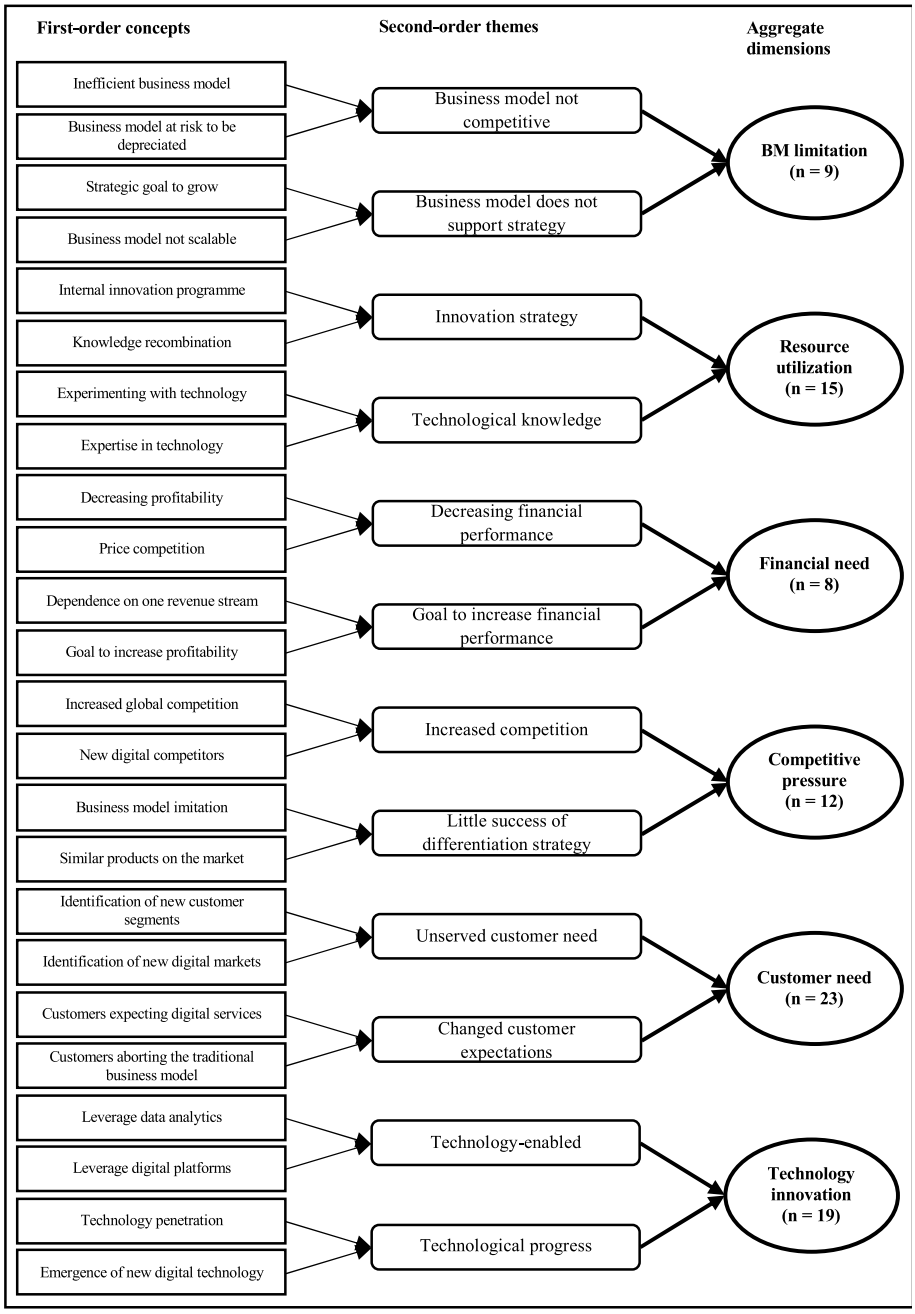

Fig. 3. Data structure (cf. Gioia et al., 2012).

csQCA, as shown in Fig. 2. First, we conducted a case survey (Larsson, 1993) on digital BMI, based on 49 cases, to identify sensed antecedents and seized digital BMIs. The case survey method allows us to compare and generalize findings from extant research on digital BMI (Larsson, 1993) to populate the boxes in Fig. 1. Second, we conducted a csQCA (Rihoux and De Meur, 2009) to determine combinations of antecedents leading to digital BMI, linking the boxes in Fig. 1. The csQCA reveals how the same antecedents in different combinations produce different outcomes (Fiss, 2011). Third, we used inductive reasoning, alternating between the resulting configurations, case information, and extant literature on dynamic capabilities and BMI to understand the configurations and develop a theoretical model (Park et al., 2020).

Case survey

Data collection

We searched for digital BMI case studies following the guidelines by Webster and Watson (2002). We consulted the three scientific databases – Web of Science, Scopus, and the AIS eLibrary – to select case studies.[1] The research terms were taken from Foss and Saebi (2017) and supplemented with the term "disruptive," which proved relevant in the initial literature search. We used inclusion and exclusion criteria to filter the initial results (Larsson, 1993) and only included case studies that described a digital BMI. The case studies also included antecedents (such as changing customer needs), leading to the digital BMI. We enriched published cases with secondary, available information from the firms' press releases, articles in relevant newspapers, and public interviews with informed experts to aim for data triangulation. Eventually, we selected 49 cases from 44 articles for analysis. We collected supplementary information such as headquarter location, firm size (i.e., employees, revenue), industry, year of the BMI, and technologies relevant to the BMI. We used this supplementary information to control for potential biases in our case sample.[2]

Category development

We inductively coded the 49 cases comprising the articles and secondary data through open, axial, and selective coding (Corbin and Strauss, 1990) to derive the sensed antecedents of digital BMI in the cases. We classified the antecedents that firms sensed before seizing them by innovating their BM (e.g., Daimler sensed that the traditional sales-based BM might not be future-proof and new customers can be reached by introducing a car-sharing platform BM). One of the authors first extracted the quotes from the text and developed open codes as first-order concepts (e.g., Daimler's BM was at risk of being depreciated). We then reduced similar open codes to axial codes representing second-order themes (e.g., BM is not competitive). Using selective coding, these codes were iteratively developed until they were distinct and mutually exclusive toward aggregate dimensions (e.g., BM limitation). This is crucial since we used these codes as conditions in the following csQCA. Fig. 3 represents the data structure (Gioia et al., 2012), providing an overview of the category development. We also classified the themes as either "organizational" (such as limitations in the BM) or "environmental" antecedents (such as the emergence of technology innovations), depending on whether they originated inside or outside the firm.

Set-Theoretic analysis

Data coding

After we had developed and defined the antecedents of BMI, we coded the conditions to create the dataset for the csQCA. We coded binary ("crisp") since we rely on secondary data analysis that does not allow us to differentiate scaled or fuzzy levels. In our csQCA, a "1" indicates the presence of the coded antecedent, while a "0" indicates its absence. Hence, one case may have several but at least one condition coded as "1" while all others are coded as "0".

To code the outcome describing the digital BMIs, we followed a defined coding scheme based on the BMI typology of Foss and Saebi (2017), describing four types of BMI. We coded four binary outcome variables describing which type of BMI resulted from the antecedents. Hence, one case can have only one outcome variable coded to "1." The second author then verified the resulting codes to validate the synthesis process. In case of ambiguity, the collected case information was re-examined and discussed. We went through all cases iteratively, building on the constant comparison.[3]

csQCA

Following Rivard and Lapointe (2012) and Henfridsson and Bygstad (2013), we performed csQCA on our binary-coded dataset to identify configurations of sensed antecedents and how firms seized those antecedents represented by the four types of BMI. Hence, the resulting configurations uncover the connection between sensing and seizing in digital BMI.

QCA is suitable for deriving cause-effect relationships based on case analysis (Fiss, 2007; Ragin, 1987). Instead of correlations that support variance-based methods, QCA uses Boolean algebra and configurational relationships to find configurations consisting of multiple interdependent causal conditions and their relative importance towards an outcome (Fiss, 2007; Ragin, 2009). Conditions refer to independent variables in variance-based methods, and outcomes represent the dependent variable. The set-theoretic character of QCA allows us to account for the complexity and inherent dynamics in digital environments and the non-linear behaviors of digital BMI (Benbya et al., 2020; Fiss, 2007). It reveals how the same antecedents in different configurations yield different outcomes (Fiss,

[1] We searched for the terms in the topic (in Web of Science) or the papers' title, abstract, or subject (in Scopus and AIS eLibrary). In addition, we filtered for peer-reviewed articles from journals, conference proceedings, or books published in English. We excluded reviews and editorial material. Table A-1 in Appendix A lists the explicit search terms and the results obtained from the databases.

[2] Table B-1 in Appendix B lists the included cases and their sources from academic papers. Table B-2 in Appendix B presents the collected descriptive case information.

[3] The resulting case coding, which serves as input data for the csQCA, is attached in Appendix C.

2011), in our case, digital BMI. It follows that QCA considers asymmetrical relationships: while the presence of a condition in one configuration may lead to the desired outcome, the absence of this condition may also be necessary for the outcome in combination with other conditions in another configuration.[4]

Combining a case survey with csQCA overcomes both methods' shortcomings, as demonstrated by Rivard and Lapointe (2012) and Henfridsson and Bygstad (2013). One major shortcoming of the case survey method, when applied in combination with variance-based statistical analysis, is that this analysis relies on the number of cases available for the chosen research question (Larsson, 1993). A medium number of cases (n = 12– 50) limits the scientific contribution based on limited insights and often low statistical significance. csQCA's advantage of information-rich results provides fruitful ground for empirical sound theorizing but works well with a medium number of cases, which are not always feasible to conduct (Greckhamer et al., 2018; Soto Setzke et al., 2020). Analyzing a sample of published case studies using csQCA allows us to build on existing research findings to identify sensing-seizing configurations for digital BMI.

Conducting a csQCA consists of several steps, of which we explain the relevant terms and our methodological choices below.[5] We have already described the data collection, derivation of conditions, data coding, and data calibration to values between 0 and 1. Thus, we continued with analyzing the necessary conditions for the four outcomes. QCA allows the distinction between necessary and sufficient conditions, whereas conditions in variance-based methods are always both necessary and sufficient (Fiss, 2007). Necessary conditions are conditions that are always present when the desired outcome is achieved. Hence, the outcome is never achieved if the necessary condition is not present. Sufficient conditions indicate that the outcome is always achieved when a condition or configuration of conditions is present. To test for necessary conditions, we used a consistency threshold of 0.90 and a coverage threshold of 0.60 (Mattke et al., 2022). Coverage indicates the empirical relevance and effectiveness of the configurations toward the outcome (Fiss, 2007). For crisp datasets, this equals the proportion of cases yielding the outcome represented by the configuration (Greckhamer et al., 2018). Consistency represents the ratio of similar cases leading to the same outcome; its role is comparable to the p-value in variance-based methods. The cut-off thresholds define the minimum value needed to detect necessity or sufficiency. For example, with a coverage threshold of 0.6, a necessary condition needs to yield the outcome for at least 60 % of cases. The analysis revealed no necessary conditions for our outcomes.

Next, we constructed the truth table that lists all possible configurations.[6] For our six conditions, the table consists of 64 (two to the power of six) rows. We observe 21 different configurations in our data. Since we observed that all antecedents lead to all four outcomes (with one exception: financial neediness is not an antecedent for adaptive BMI), there is no contradiction with our understanding ("difficult counterfactuals") of antecedents of digital BMI in the 43 residuals. Therefore, we classify them as "easy counterfactuals," meaning that they can lead to one of the four types of BMI and can be used to simplify the solutions in logical minimization (Ragin and Fiss, 2008).

To identify sufficient configurations, csQCA uses logical minimization. Like the necessity analysis, the sufficiency analysis builds on the consistency and minimum frequency threshold. Frequency refers to the number of cases representing a configuration. As recommended in the literature, we set the consistency threshold to 0.75 (Mattke et al., 2022). We set the frequency threshold to 1 following the recommendations given in the literature for small and medium-sized case samples (Greckhamer et al., 2018; Soto Setzke et al., 2020). This is also in line with the argumentation that configurations covering few cases can still be relevant if they present novel or unexpected insights (Schneider and Wagemann, 2010).

To minimize the truth table, we used the intermediate and parsimonious solutions (Ragin, 2009). The two solutions differ in the degree they include counterfactuals in the minimization.[7] Since we defined four different outcome variables representing the four BMI types, we performed the logical minimization eight times (two minimizations per outcome). Following Fiss (2011), we defined core conditions present in both solutions and peripheral conditions only present in the intermediate solution. Core conditions thus remain part of the solution even if counterfactuals occur and possess a higher relevance for achieving the outcome.

Inductive reasoning

Last, we revisited the individual cases when analyzing the configurations to understand the circumstances under which these configurations emerge, as suggested by Park et al. (2020). We iterated between the configurations, case information, and extant

[4] For example, Park et al. (2017) found by conducting a fuzzy-set QCA that both the presence of organization size (= large organization) and its absence (= small/medium organization) lead to decision-making agility; however, only in combination with the presence (for large organizations) or absence (for small organizations) of the effective usage of communication technology. Hence, they concluded that decision-making agility in large organizations relies on effective communication technology while small and medium-sized organizations do not. To identify sensing-seizing connections, these properties of QCAs are better suited than variance-based models.

[5] For detailed guidance on the application of QCA in IS research, we refer the reader to Mattke et al. (2022), Park et al. (2020), and Soto Setzke et al. (2020), who helped us with our application.

[6] The aggregated truth tables are in Appendix D.

[7] The parsimonious solution includes all counterfactuals to minimize the truth table and thus produces the most minimalized (i.e., most parsimonious) solution. The intermediate solution includes counterfactuals based on an expectation vector provided by the researcher. Since we observed all of our conditions for all four different outcomes in our case sample, we expected the presence of all conditions to yield any outcome. QCA also provides a third type of minimization, producing a complex solution. The complex solution does not consider any counterfactuals and thus only provides configurations observed in the dataset. For our goal of creating a theoretical model of sensing-seizing connections for digital BMI, we did not consider this a suitable approach because we wanted to acknowledge the presence of configurations not observed in our case sample.

Table 1
Categories for sensing and seizing digital BMI.

		Category	Explanation	Example	E	A	F	C	N (%)
Sense: Antecedents	*Organizational antecedents*	*Business model limitations*	Recognizing that a new BM is more suitable for further growth or the future business environment	Donkey Republic	4	1	1	3	9 (18 %)
		Resource utilization	Specific capabilities and knowledge that could be exploited in a digital BMI	Apple	5	4	3	3	15 (31 %)
		Financial need	Facing shrinking financial indicators (e.g., profit) or opportunities to improve financial performance	Lufthansa	3	0	3	2	8 (16 %)
	Environmental antecedents	*Competitive pressure*	Market participants or new entrants putting pressure on a firm's BM	Ericsson	4	5	1	2	12 (24 %)
		Customer need	Identification of a new or changed customer need or an entire market that can be served	Uber	4	5	6	8	23 (47 %)
		Technology innovation	The ascendance of new technology provided a way to rethink the firm's BM	IBM	5	5	5	4	19 (39 %)
Seize: Digital BMI		*Evolutionary*	Fine-tuning of individual BM sub-systems	Donkey Republic					15 (31 %)
		Adaptive	Changes to the whole BM that are new to the firm but not to the industry	Apple					10 (20 %)
		Focused	Innovation in individual BM sub-systems that are an innovation to the industry	Uber					12 (24 %)
		Complex	Innovation of the whole BM that is new to the industry	Hilti					12 (24 %)

Table 2
Sensing-Seizing Configurations in Digital BMI.

Configuration		**Outcome: Digital BMI type**									
Antecedent		Evolutionary				Adaptive			Focused		Complex
		E1	E2	E3	E4	A1	A2	A3	F1	F2	C1
Organizational antecedents	BM limitation			●	●	⊗	●				●
	Resource utilization		●		●	●					⊗
	Financial need	●					⊗		●	●	
Environmental antecedents	Competitive pressure	●		⊗			●	●	⊗		
	Customer need	⊗	⊗	⊗	•	●			●		●
	Technology innovation		●			⊗		●		●	
Consistency		1	1	0.75	1	1	1	1	1	1	1
Unique coverage		0.2	0.133	0.2	0.067	0.2	0.1	0.2	0.083	0.083	0.25
Raw coverage		0.2	0.133	0.2	0.067	0.2	0.1	0.2	0.083	0.083	0.25
Cases		16, 18, 28	1, 42	8, 14, 34, 41	44	11, 46	26	3, 25	24	43	29, 32, 40
Solution consistency		**0.9**				**1**			**1**		**1**
Solution coverage		**0.6**				**0.5**			**0.167**		**0.25**

Black circles "●" indicate the presence of a condition, and empty circles "⊗" indicate its absence. Large circles indicate core conditions; small ones peripheral conditions. Blank spaces indicate irrelevance.

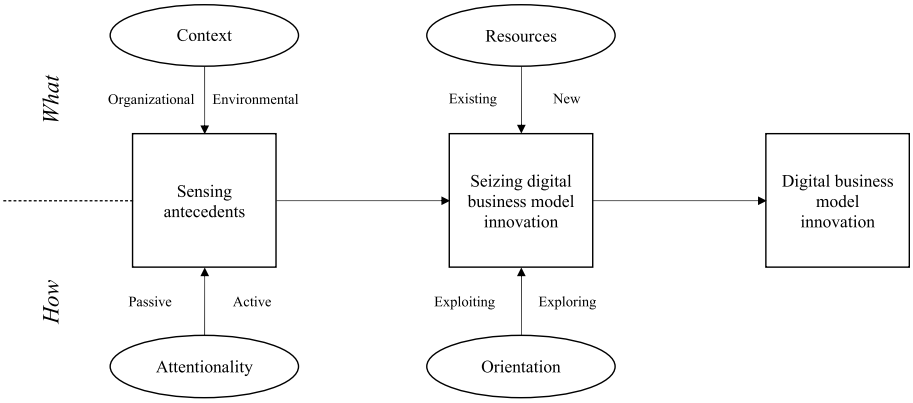

Fig. 4. Connecting sensing and seizing for digital BMI.

literature to develop a theoretical model connecting sensing and seizing for digital BMI.

Results

Categories for sensing and responding in digital business model innovation

We identified six sensing categories from the case survey and four seizing categories from the literature. The sensing categories comprise *organizational* and *environmental* antecedents, which indicate the origin of the sensed change. *Organizational* antecedents cover reasons such as current BM limitations, resource utilization, and financial needs for innovating within the firm. *Environmental* antecedents refer to external changes, such as competitive pressure, changing customer needs, and technological innovation that require seizing digital BMI. Table 1 summarizes the sensed and seizing antecedents through BMI, the identified categories, a brief explanation, and an illustrative example based on the cases.[8] The table also shows the frequency distribution of sensing-seizing combinations within our sample's 49 cases (columns "E" = evolutionary; "A" = adaptive; "F" = focused; "C" = complex) and the total number of occurances in the case sample "N". It shows which antecedent changes lead to which type of BMI. We observe an almost equal distribution of the four innovation types, ranging from 10 (20 %) cases to 15 (31 %) cases. The antecedent changes range from eight occurrences (16 %; financial need) to 23 (47 %; customer need).

Sensing-seizing configurations

Based on the csQCA, we reveal ten sensing-seizing configurations (see Table 2). The configurations show which combination of

[8] Appendix E gives a detailed explanation of all categories.

specific organizational and environmental antecedents can be seized by different digital BMIs. We find effective configurations for the two seizing outcomes of evolutionary and adaptive BMIs, explaining 60 % and 50 % of the case sample. Our configurations explain 16.7 % and 25.0 % for focused and complex BMIs. All configurations show high consistency (i.e., 0.9 or 1), expressing a robust empirical foundation in our case sample, above the suggested threshold of 0.80 (Ragin, 2009). Hence, our solution quality is comparable to other IS research, such as Park et al. (2017), Lee et al. (2019), Koo et al. (2019), and Bui et al. (2019).

We explored how the sensing of antecedent configurations leads to seizing different types of BMI by revisiting the cases and extant literature. To illuminate the connection of sensing and seizing, we differentiate the "what" and "how," as depicted in Fig. 4. The "what" describes the context of the sensed antecedents (organizational or environmental) and the resources used (existing or new resources) in their seizing. The "how" describes the attentionality (active or passive) toward the antecedents and the strategic orientation (exploiting or exploring) when seizing BMI. All four influence the digital BMI type; different combinations then explain the differences between types.

Context describes the sensed antecedents' origin, thus what is sensed (Park et al., 2017). Organizational antecedents cover reasons for innovating within the firm. Environmental antecedents refer to external changes, such as changing environments, that require seizing opportunities with a digital BMI. *Attentionality* describes "how sensing possibilities for action is about being exposed and attuned to corresponding flows of action" (Baygi et al., 2021). Active sensing thus refers to exploring opportunities, challenging existing BMs, and sensing change ahead of competitors (Gambardella and McGahan, 2010; Sawhney et al., 2006). Passive sensing refers to sensing natural changes evolving to fine-tune the strategy as organizations are exposed to change.

Seizing sensed change alters the firm's *resources* (Doz and Kosonen, 2010). Extant resources are linked in a novel way by redeploying unchanged resources. Redeploying existing resources strengthens dynamic capabilities, supporting responsiveness (Ravichandran, 2018). In contrast, deploying new resources into adapted BMs is a key micro-foundation of dynamic capabilities (Teece, 2010). The *orientation* describes how these resources are changed, differentiating between exploiting and exploring new BMs to alter the firm's competitive position. An exploiting orientation leverages the sensed antecedents to keep the firm's position and increase its efficiency (Osiyevskyy and Dewald, 2015). On the other hand, an exploring orientation refers to seizing the change in its BM to reposition itself in a more advantageous market position instead of competing in an unfavorable position (Tanriverdi et al., 2010).

Evolutionary digital business model innovation

The csQCA reveals four combinations of antecedents that lead to evolutionary BMI (E1–E4). Evolutionary refers to the fine-tuning of individual BM sub-systems (Foss and Saebi, 2017). These small changes affect individual aspects of a BM and express a small degree of novelty. The sensed antecedents for these configurations mainly originate from an organizational context. While the configurations include environmental antecedents, the case analysis reveals that firms only sense the need for BMI when consequences emerge within the organization. This also implies that firms implementing evolutionary BMI do not proactively search for BMI opportunities but recognize BMI as a solution to an emerging threat. Therefore, the BMI primarily builds on transforming existing resources to exploit the firm's competitive position.

In E1, we see a combination of competitive pressure and financial need with unchanged customer needs. This combination shows competitive markets with strong market participants and a low potential for product differentiation. Consequently, the competition is based on price differentiation, which leads to shrinking profits. However, some firms reconfigure their existing resources for small BM changes and, thus, for differentiation. For example, instead of competing with prices, Allianz Suisse changed from standard car insurance with periodical payments to usage-based pricing, using car sensors and usage data (Bucherer et al., 2012; Desyllas and Sako, 2013).

E2 represents a combination of resource utilization and technology innovation with unchanged customer needs. Using their existing capabilities, knowledge, and other resources, firms respond to technological advancements. For example, IBM has fundamental capabilities in hardware. They innovated their BM from hardware sales and services to integrated management consulting. As revenues from hardware sales decreased, IBM used its IT integration and solution provisioning knowledge to become a technology and business consultancy (Jetter et al., 2009).

The third solution leading to evolutionary innovation, E3, comprises firms that sensed emerging limitations in their original BM without being exposed to competitive pressure or changing customer needs. For example, the bike-sharing startup, Donkey Republic, recognized the limited scalability of its original peer-to-peer-sharing BM. As a result, they implemented a platform-based BM, matching local bike rentals with customers, seizing the technological opportunity through exploitation, and addressing the BM limitation (Winslow and Mont, 2019).

The fourth configuration, E4, is the only evolutionary innovation that responds to a change in customers' needs, combined with BM limitations and resource utilization. The configuration represents a change in customer needs that cannot be served with the existing BM. However, capabilities and resources to meet the customer needs exist in the firm. In our sample, one anonymous case responded to this situation by exploiting separated value propositions into one digital platform BM (Mezger, 2014).

Adaptive digital business model innovation

Adaptive BMI shows fundamental changes to the entire BM: new to the firm but not the industry (Foss and Saebi, 2017). The sensed antecedents for adaptive BMI originate from organizational and environmental contexts where firms sense that their current BM does not align with environmental changes and requires modification. Again, this need for BMI is only sensed when it already affects the current BM. The seizing builds on the existing resources complemented with new resources or capabilities for the innovated BM. Similarly, the BMI is oriented toward exploiting the competitive position, but firms also leverage the architectural change of the BM to reposition to explore a new competitive position. We find three combinations of antecedents (A1, A2, A3) that lead to adaptive digital

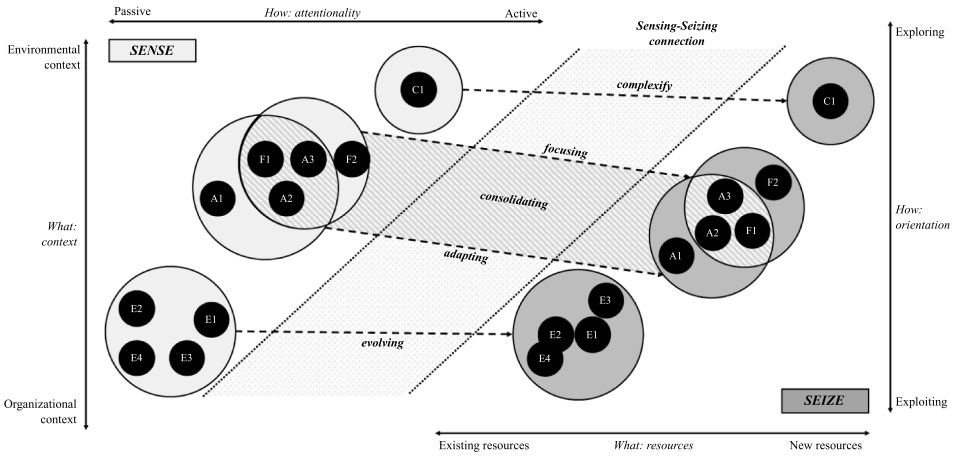

Fig. 5. The connection of sensing and seizing for digital business model innovation.

BMIs.

As part of the sensing-seizing configuration A1, firms sensed the opportunity for digital BMI from noticing emerging BMs that serve a new customer need. They sensed no need to appropriate new technologies, since they already possess the required organizational resources and digital infrastructure. There was no threat or limitation from the current BM as it was still profitable. For example, when Apple launched iTunes, there were already online music shops in the market. However, Apple sensed an opportunity to build a solution with a better user experience by exploiting their design and technology knowledge and resources (Park, 2011).

In contrast to A1, firms in configuration A2 sensed rising competitive pressure and limitations in the current BMs but without a pressing financial need. An anonymous IT provider sensed new, strong, international competitors entering their market with cloud computing BMs. Their traditional product sales and service BM hindered the expansion of their customers to international and small local businesses. Adopting a cloud service BM and the required digital infrastructure allowed the firm to use existing resources more efficiently, remain competitive, and even expand its customer base (Ahokangas et al., 2014). The observation of competing firms with innovative BMs drove the discovery of digital BMI to escape the threatening competition.

Following the slogan "offense is the best defense," A3 cases sensed technology innovations enabling digital BMI to escape arising competitive pressure. For example, Ericsson seized the emergence of cloud computing by actively exploring the opportunities and threats to their BM. Before it could become a threat, they adopted a cloud infrastructure that allowed them to exploit existing and explore new resources to iteratively adapt their BM and organizational structures to become a cloud firm (Khanagha et al., 2014).

Focused digital business model innovation

We identified two configurations (F1, F2) for seizing focused digital BMI, which changes specific elements of the BM (e.g., value delivery) that are new to an industry (Foss and Saebi, 2017). Both configurations show firms that face financial needs. Firms actively probed opportunities outside the organization to solve this problem and found new customer segments to serve or new technologies to integrate. They also deployed new resources to create the BMI. As with adaptive BMIs, firms pursued focused BMIs to exploit their competitive position, but the degree of novelty in the new BM creates a forward orientation, exploring an improved competitive advantage.

The first configuration, F1, is caused by firms sensing declining revenues because of changing customer needs. The existing BM was not under competitive pressure, and the firms could have sustained themselves without BMI. Firms in this configuration only require a focused BMI to exploit their strengths and address new customer groups. In one case, Dow Corning actively figured out that the need for cheap standardized products was not served but could complement its stagnating premium service-oriented offering. Dow Corning seized the BMI by deploying a new digital infrastructure in the form of an online store. This in turn allowed the firm to not only exploit this platform by offering a more cost-effective offering, but also to explore new opportunities to reach new customers with the new BM.

The second configuration for focused digital BMI, F2, combines a financial need with technology innovation as antecedents. Whereas a financial need typically occurs due to shrinking profits, leveraging technology innovation can reduce costs or enable new opportunities. Unlike F1, but similar to A3 (which also utilizes technology innovation), seizing this antecedent configuration, which explores a new technology to solve a financial need, provides firms with the opportunity to explore technological innovation to complement existing digital infrastructure. The resulting changes to the BM are small but pivotal. In the case of THA Group, for example, a change in the payment system for home care services led to a decline in revenue, forcing THA Group to look for ways to reduce costs or otherwise increase revenue. They added a new digital monitoring solution that complements their resource base and pivots their BM from in-person service delivery to around-the-clock, data-driven remote service (Singh et al., 2011).

Complex digital business model innovation

Finally, one configuration shows the antecedents of complex digital BMIs. A complex digital BMI creates an entirely different BM

Table 3
BMI Typology Extension.

		Evolving	Adapting	*Consolidating*	Focusing	Complexify
Sensing	**Context**	Organizational			Environmental	
	Attentionality	Passive			Active	
Seizing	**Resources**	Existing resources			New resources	
	Orientation	Exploiting			Exploring	
Role of digital technology		BM first	BM first	Tech. first	BM first	Tech. first
Foss and Saebi (2017)	**Novelty**	New to the firm		New to the industry		
	Scope	Modular	Architectural	Modular	Architectural	
		Evolutionary	**Adaptive**	**Focused**	**Complex**	

that is new to the industry and severely impacts its environment (Foss and Saebi, 2017).

Configuration C1 shows that firms create a complex digital BMI when they sense both limitations in their initial BM and a changed customer need but do not possess the internal resources to implement the BM before seizing it. The sensed context lies in the firm's environment as it recognizes that the current BM will not serve future customer needs and is thus at risk of being disrupted. This future customer need is sensed only by active attentionality. The complex digital BMI is built through experimentation and iterative learning, which deploys new resources in the firm. In our case sample, we observed this situation in the case of Daimler. The traditional BM for car sales will not meet the future needs of customers who do not want to own a car for a variety of reasons, such as using more sustainable public transport (Spickermann et al., 2014; Willing et al., 2017). To counteract the projected declining car sales, Daimler explored the opportunity for a new free-floating car sharing BM. To become a platform owner in this new BM, Daimler had to build an entirely new resource base in a new organization (Bucherer et al., 2012). The complex BMI provided an opportunity to explore their early competitive position, which is important in platform competition.

The connection of sensing and seizing for digital BMI

Despite the relevance of dynamic capabilities for digital innovation, ways to connect sensing and seizing change for superior economic performance or competitive advantage remains scarce (Ravichandran, 2018; Schilke et al., 2018). By articulating the ten configurations along four dimensions, we show how firms connect sensing and seizing to create digital BMIs. Fig. 5 positions the configurations along with the causal connection of sensing (*top-left*) and seizing (*bottom-right*). The corridor in-between (*dotted area*) highlights the connection of sensed antecedents and seized digital BMI. The sensing-seizing connection for digital BMI results in the corresponding BMI type exposing how firms sense which antecedents determine how firms seize digital BMI.

The initial step for BMI is sensing an opportunity or need that can be addressed by a new BM (Teece, 2018a). Sensing involves the context of what is sensed and attentionality to how the antecedents are sensed. Theory often references changed or unfulfilled customer needs and technological progress as the sensed antecedents of BMI (Foss and Saebi, 2017, 2018). Based on the antecedent configurations yielding digital BMI, what is sensed ranges from the organizational context within the firm, such as BMs not supporting the firm's long-term strategy, or the environment external to the firm, such as changing customer needs and technology innovation. Sensing differs in how firms identify these antecedents, as this can be done actively or passively. At one extreme, this means that a firm actively creates a digital BMI opportunity by developing new technology, such as when Kodak developed digital photography (Lucas and Goh, 2009). At the other extreme, the firm (e.g., a retailer) remains passive in identifying BMI opportunities until the need can no longer be ignored (e.g., to have an online store).

In seizing digital BMI, firms address these sensed antecedents by creating, extending, or modifying their resources (Teece, 2018a). Thus, firms can use existing and new resources in the process of seizing by exploiting and exploring the new BM. Firms seize the new BM differently depending on their previous resource base, including their physical and technological resources, knowledge, and capabilities. Building on the existing resource base, firms reconfigure their resources for the BMI or augment it with new resources. However, some BMIs, such as transforming to a BM based on digital photography, require the development of an entirely new resource base. This modification of resources follows an exploitation or exploration orientation. By exploitation, the firm strengthens the original BM by adopting a new BM in whole or in part (Osiyevskyy and Dewald, 2015). In exploration, the firm develops a different BM, for example, to gain a new competitive position or enter a new customer market.

For effective digital BMI, firms need to connect sensing and seizing. Otherwise, the Kodak example shows, that sensing opportunities (such as from technology innovation) can fail to seize the digital BMI opportunity and exploit the technology (Lucas and Goh, 2009). This sensing-seizing connection depends on their current situation and the changes they are sensing. Depending on the sensed antecedents, firms seize different types of BMI (Foss and Saebi, 2017, 2018; Saebi, 2015). Firms putting active attention on searching opportunities for digital BMI do so predominantly in their environment. They especially monitor their customers, both current and (potential) future. If the firm senses changes, such as the BM no longer being suitable to meet customers' needs, the current BM cannot be exploited. Firms should then seize focused or complex BMI and explore opportunities not associated with current BMs and resources (Gambardella and McGahan, 2010; Sawhney et al., 2006).

The more passive the sensing, the more the antecedents stem from the organizational context than the environment. Then, the firms sense a stagnation or even decline in their competitive position. However, if the current BM still serves the customers' needs, firms strengthen their BM and exploit extant resources and capabilities (Christensen, 1997; Markides, 2006) to evolve or adapt their BM. The resulting BMIs are natural changes to stay competitive in dynamic environments (Lanzolla and Markides, 2021).

In-between those two distinguishable sensing-seizing connections, we observe an intersection of adaptive and focused BMI in both sensing and seizing (highlighted by the striped area). Both adaptive and focused BMI position themselves in the middle between active and passive sensing, sensing environmental and organizational changes affecting the current BM. Seizing balances exploration and exploitation of both existing and new resources. While this sensing-seizing connection seems contradictory at first, it can be explained when looking at the firms at this intersection.

The key to resolving those contradictions lies in the role of technology and how firms at this intersection adopt new digital infrastructure[9] to undergo a digital BMI. We name this novel type of BMI as "consolidating." Firms consolidate technology toward a digital infrastructure, such as cloud computing, that allows them to exploit (e.g., reducing costs) and explore (e.g., pay-*per*-use payment) new BMI opportunities. Based on this consolidation and reduction of complexity, firms can undergo further adaptive BMI (constantly exploiting new infrastructure horizontally to become more efficient) and focused BMI (exploring new affordances of the infrastructure vertically). Sensing describes then how each of the further steps is being triggered.

After the consolidation to a digital BM infrastructure, there are distinct sensing-seizing connections for adaptive and focused BMI. For example, Apple's introduction of iTunes exploited the existing digital infrastructure for developing software and managing online transactions, expanding horizontally. Based on such infrastructure and consolidating BMI, firms are implementing focused BMI by using specific digital technologies that focus on solving a particular problem and pivot a single BM element, such as THA Group's remote monitoring solution to solve the problem of rising costs.

We extend Foss and Saebi's (2017) dimensionalization of the BMI construct (i.e., novelty and scope), with the dimensions of BMI creation emerging from the connection of sensing and seizing (i.e., context, attentionality, resources, orientation). There are four types of BMI (evolutionary, adaptive, focused, and complex) in terms of novelty and scope (Foss and Saebi, 2017). However, for firms leveraging digital technology for digital BMI, there are five ways to create these types of BMI in the sensing-seizing connection, listed in the header of Table 3. Every BMI type has a distinct sensing-seizing connection, which we added to Foss and Saebi's (2017) BMI typology resulting in Table 3. The fifth connection, which we call consolidating BMI, deploys the technological basis for further adaptive or focused BMI. It differentiates the role of digital technology. Consolidating BMIs put digital technology first, fundamentally changing the value creation to enable radically new BMIs that eventually become disruptive (Christensen, 1997; Lucas and Goh, 2009). In evolving, adapting, and focusing BMIs, digital technology complements a salient BM to provide economic benefit (Al-Debei and Avison, 2010; Chesbrough, 2007; Weber et al., 2021; Weking et al., 2020b).

Theoretical contributions

This work sheds light on the connection between sensing change and seizing digital BMI. Neither sensing nor seizing capabilities alone are sufficient to profit from change (Ravichandran, 2018; Tallon et al., 2019). However, the differences in firms' approaches to creating and capturing value in dynamic and digital environments reside in translating what has been sensed into how a digital BMI is seized (Foss and Saebi, 2017, 2018; Saebi, 2015). Thus, the connection of specific sensed antecedents with particular seizing strategies reveals the mechanisms underlying digital BMIs and the role of dynamic capabilities enabling firms to innovate their BM (Chesbrough, 2007; Foss and Saebi, 2017; Teece, 2010).

This study makes several contributions to the BMI and digital business strategy literature. First, it explains why firms engage in digital BMI. Most BMI research has focused on the importance of BMI in managing change, such as digital transformation and its economic outcomes (e.g., Rai and Tang, 2014; Saebi, 2015; Teece, 2010), overlooking how BMI responds to different antecedent contexts (cf. Foss and Saebi, 2018; Saebi, 2015). Thus, pathways to digital BMI remain unclear. We looked at the antecedents that firms sensed and responded to by seizing different types of digital BMI. This study explains how the connection of sensing and seizing results in four different types of BMI, as conceptualized by Foss and Saebi (2017). We introduce consolidating BMI as a new type of BMI unique to the digital context, enabling firms to adopt a new BM and subsequent digital BMIs based on a renewed digital infrastructure. The sensing-seizing connections, shown in Fig. 5, indicate what firms do to achieve the different types of BMI. Thus, even though these connections are not fully prescriptive, they show what firms are supposed to do to innovate their BMs in a certain way. For example, while the predominant technologies in our sample are digital platforms, mobile apps, and cloud computing, we argue that the connections will apply similarly to new digital technologies, such as artificial intelligence. Therefore, this study contributes to a prescriptive BMI theory. It complements literature on innovative BMs formulated in BM taxonomies (e.g., Weber et al., 2021; Weking et al., 2020a). Whether the firm has consolidated its BM and digital infrastructure to enable further adaptive and focused BMI, the digital BM taxonomies apply differently to focal BMIs.

Second, the connection of sensing and seizing for digital BMI theorizes how firms leverage dynamic capabilities for different types of BMI. This goes beyond how to build dynamic capabilities and moves toward connecting sensed antecedents with seizing strategies. These connections expand our understanding of what capabilities are needed for sensing and seizing, such as Battistella et al. (2017). We show that the emergence of different BMI types cannot be solely explained by the antecedents causing a firm's decision to innovate their BM, but the combination of what and how these antecedents are sensed and seized. Scholars building on dynamic capabilities theory need to acknowledge such connections when explaining the change, innovation, or the creation of competitive advantage.

[9] Teece (2018b) refers to these technologies as "enabling technology" that "are capable of ongoing technical improvement; and enable complementary innovations in application sectors." This builds on Martin's (1993) notion of "generic technologies" whose exploitation will "benefit a wide range of sectors of the economy and/or society.".

Practical implications

Strategy is about what the firm chooses to do and not to do; it is about sensing changes within and outside the organization and deciding whether and how to seize them (Gavetti and Rivkin, 2005). As firms struggle to innovate their BMs (Chesbrough, 2007; Teece, 2010), our results support analogical thinking for strategists (Gavetti and Rivkin, 2005). Knowledge about how possible BM innovations can seize sensed antecedents helps firms make appropriate decisions when sensing change. Firms can draw their evaluation from our sensing-seizing connections, configurations, and individual cases, providing different pathways to digital BMI. Thus, firms can effectively leverage their resources and capabilities on a designated path for designing and experimenting with new digital BMs.

Limitations

Combining the case survey method and csQCA mitigates some shortcomings of both approaches. Analyzing a sample of published case studies using csQCA allows us to build on existing research findings, considering the antecedents and understanding digital BMI's complexity and dynamic capabilities. Nevertheless, our research faces some limitations. First, our analysis relies on secondary data derived from case studies. We used inclusion and exclusion criteria to select cases with rich information and triangulated the data to aim for an adequate understanding of the cases. However, the cases originally served a different purpose and focused on different aspects of digital BMI that we cannot understand in-depth; thus, we used only a few cases that explicitly focused on dynamic capabilities and the implications of change. We include the coding of the cases in Appendix C for researchers to question our coding and comprehension. Second, the quantification of qualitative case data necessarily results in information loss (Larsson, 1993). This is conveyed by the number of cases (49) and the use of QCA, which emphasizes the in-depth case analysis, to analyze our configurations. We coded the information binary, only accounting for the presence of an antecedent. Hence, it is not possible to compare the impact strength of antecedents. We must acknowledge that our analysis was performed at a high level and does not aim for exceedingly detailed analyses of each case.

Future research

This study warrants several avenues for future research on digital BMI. First, empirical research can build on our findings to refine digital BMI moderators, thus further extending the BMI typology. The differences in connecting sensing and seizing digital BMI may manifest in variances in firm-level moderators, such as entrepreneurial behavior, culture, or cognition (e.g., Aspara et al., 2013; Doz and Kosonen, 2010; George and Bock, 2011). On an ecosystem level, the pathways may be impacted by digital BMIs in the ecosystem or the economy (Floetgen et al., 2021; Teece, 2018b). Second, quantitative studies can further refine our set-theoretic approach by examining the strength of relationships between sensed antecedents and the seized BMI. Third, the role of technology innovation for digital BMI requires further clarification. As we argued, the application of digital BM taxonomies differs for firms depending on their context. Future BM taxonomy research could emphasize this difference when providing recommendations on innovating the BM based on the investigated digital technology.

Conclusion

Dynamic capabilities are highly relevant to the environmental changes caused by digital transformations, and digital BMIs are essential for thriving amidst the ongoing transformations. As previous research shows, sensing and seizing are interrelated components of dynamic capabilities. This paper explains how firms connect sensing and seizing for digital BMI based on a configurational analysis. Thereby, we extend the BMI typology by Foss and Saebi (2017) with the perspective of how different types of BMI emerge and find one new type unique to the digital context. The connection of sensing and seizing shows that pathways to digital BMI depend on the digital infrastructure that has been built in these consolidating BMIs and that enables different future directions of digital BMI.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Explanation of research methodology

See Table A1.

Table A1
Search terms and database hits.

Database Search term	Web of Science	Scopus	AIS Electronic Library*
"business model innov*"	818	1,086	98
"innov* business model"	143	617	100
"business model transform*"	26	60	0
"transform* business model"	4	34	44
"business model renewal"	6	11	5
"business model reinvention"	2	2	0
"business model evolution"	29	47	30
"business model dynamics"	8	26	81
"disruptive business model"	16	71	15
"business model disruption"	5	8	15
Unique per database	955	1,785	238
Unique	1,850		
Full-text analysis	233		
Covering digital BMI	67		
Covering antecedents of BMI	44		
Selected for analysis	**44**		

* The search of the AIS Electronic Library does not function with wildcard searches(*). Search terms with * at the end waived the wildcard. Search terms with * in the middle of a term were divided into two terms linked with the AND operator (e.g., "transform" AND "business model").

Appendix B. Case sample

Within the sample of 49 firms listed in Table B1, most headquarters are located in Europe (22), followed by 14 in the USA and eight in Asia. Two firms were located in Oceania and one in the UAE. The firms were mainly active in ICT (9), media (9), manufacturing (7), mobility (5), and retail (5). Other industries include finance (3), health (2), insurance (2), and telecommunication (2). The sample covers a wide range of firm sizes (revenue and employees), ranging from below US$10 M to above US$500B (avg.: US$65B: US$16B) and from 100 to more than two million employees (avg.: 160,000; median: 36,000). (SEE Table B2.).

Table B1
Case sample and references.

No	Case	Reference
1	Progressive Corporation	Desyllas and Sako (2013)
2	China United Telecommunication Corporation	Wu et al. (2013)
3	Anonymous (Ericsson)	Khanagha et al. (2014)
4	Anonymous	Velu (2016); Velu and Stiles (2013)
5	Suning Appliance Company Limited	Cao (2014)
6	Uber	Khare et al. (2016); Watanabe et al. (2016)
7	Edeka	Zolnowski et al. (2014)
8	100percent	Newth (2016)
9	Anonymous	Velu (2017)
10	Cyberlibris	Laïfi and Josserand (2016)
11	Apple (iTunes)	Park (2011); Purkayastha and Sharma (2016)
12	Philips	Brock et al. (2019)
13	Walmart	Lv and Liu (2012)
14	Donkey Republic	Winslow and Mont (2019)
15	Salesforce	Snihur et al. (2018)
16	eBay Classifieds	Comberg and Velamuri (2017)
17	Schindler	Wißotzki et al. (2017)
18	Lufthansa	Chen et al. (2017); Chen et al. (2016)
19	DP World	Kamoun (2008)
20	Alibaba	Tan et al. (2009)
21	Netflix	Rayna and Striukova (2016)
22	Spotify	Rayna and Striukova (2016)
23	Hilti	Johnson et al. (2008)
24	Dow Corning	Bucherer et al. (2012); Johnson et al. (2008)
25	Anonymous	Ahokangas et al. (2014)
26	Anonymous	Ahokangas et al. (2014)
27	RTL Television	Huyskens and Loebbecke (2007)

(*continued on next page*)

Table B1 (*continued*)

No	Case	Reference
28	Allianz Suisse	Bucherer et al. (2012)
29	Daimler: Car2Go	Bucherer et al. (2012)
30	e24	Bucherer et al. (2012)
31	Endress + Hauser	Bucherer et al. (2012)
32	Tencent	Dai et al. (2011)
33	Card Union Technology Co., ltd	Gou et al. (2018)
34	Card Union Technology Co., ltd	Gou et al. (2018)
35	Anonymous	Günzel and Wilker (2012)
36	Wishberry	Gupta and Bose (2019)
37	Apple	Purkayastha and Sharma (2016)
38	Anonymous	Rajala et al. (2018)
39	Rubicon Global	Rajala et al. (2018)
40	Mohawk	Stamas et al. (2014)
41	GoGet	Tan et al. (2017)
42	IBM	Jetter et al. (2009)
43	THA Group	Singh et al. (2011)
44	Business	Mezger (2014)
45	Technology	Mezger (2014)
46	Games	Mezger (2014)
47	Knowledge	Mezger (2014)
48	Printing	Mezger (2014)
49	Education	Mezger (2014)

Table B2
Collected descriptive case information.

ID	Firm	Headquarter location	Industry (primary)	Revenue (estimate)	Employees (estimate)	Startup / Incumbent	Year of BMI	Technologies
1	Progressive Corporation	USA	Insurance	$ 30.000.000.000	35,000	Startup	1999	Internet, GPS, digital maps, data analytics
2	China United Telecommunication Corporation	China	Telecom	$ 40.000.000.000	n. a.	Incumbent	2003	Internet, mobile, digital platforms
3	Anonymous (Ericsson)	Sweden	Telecom	$ 22.000.000.000	110,000	Incumbent	2009	Cloud computing
4	Unknown	USA	Finance	n. a.	n. a.	Incumbent	2002	Digital platforms
5	Suning Appliance Company Limited	China	Retail	$ 36.900.000.000	39,031	Incumbent	2010	E-commerce, digital platforms
6	Uber	USA	Mobility	$ 11.270.000.000	22,263	Startup	2009	Mobile apps, digital platforms
7	Edeka	Germany	Retail	$ 60.018.600.000	376,000	Incumbent	2013	Mobile apps, mobile payment
8	100percent	New Zealand	Social	n. a.	n. a.	Startup	2014	Digital platforms
9	Anonymous	India	Farm & Food	n. a.	n. a.	Incumbent	2007	Mobile
10	Cyberlibris	France	Education	$ 2.463.450	< 100	Startup	2001	Internet
11	Apple	USA	IT	$ 265.595.000.000	132,000	Incumbent	2003	Internet, digital platforms
12	Philips	Netherlands	Manufacturing	$ 20.290.989.750	77,400	Incumbent	2011	Internet-of-Things
13	Walmart	USA	Retail	$ 514.400.000.000	2,200,000	Incumbent	n. a.	E-commerce
14	Donkey Republic	Denmark	Mobility	n. a.	< 100	Startup	2005	Mobile apps, digital platforms
15	Salesforce	USA	IT	$ 13.280.000.000	35,000	Startup	1999	Cloud computing, digital platforms
16	eBay (Kleinanzeigen)	USA	Retail	$ 10.746.000.000	14,100	Incumbent	2004	Digital platforms
17	Schindler	Germany	Manufacturing	$ 10.414.134.900	58,271	Incumbent	2016	Cloud computing, hardware technology
18	Lufthansa	Germany	Mobility	$ 40.131.840.000	135,500	Incumbent		Data analytics
19	DP World	UAE	Logistics	$ 4.231.000.000	36,000	Incumbent	2008	RFID
20	Alibaba	China	Retail	$ 200.000.000.000	102,000	Startup	1999	Digital platforms
21	Netflix	USA	Media	$ 15.794.000.000	5400	Startup	2007	Internet, data analytics, digital platforms
22	Spotify	Sweden	Media	$ 5.980.000.000	4165	Startup	2006	Internet, mobile, digital platforms
23	Hilti	Germany	Manufacturing	$ 5.747.676.750	27,000	Incumbent	n. a.	

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Table B2 (*continued*)

ID	Firm	Headquarter location	Industry (primary)	Revenue (estimate)	Employees (estimate)	Startup / Incumbent	Year of BMI	Technologies
								Software technology
24	Dow Corning	USA	Manufacturing	$ 6.120.000.000	12,000	Incumbent	2002	E-commerce
25	Anonymous	Finland	IT	n. a.	n. a.	Incumbent	n. a.	Cloud computing
26	Anonymous	Finland	IT	n. a.	n. a.	Incumbent	n. a.	Cloud computing, digital platforms
27	RTL Television	Germany	Media	n. a.	n. a.	Incumbent	2006	Digital platforms
28	Allianz Suisse	Switzerland	Insurance	$ 4.255.050.000	3600	Incumbent	n. a.	Telematics
29	Daimler: Car2Go	Germany	Mobility	$ 187.446.150.000	298,683	Incumbent	2009	Mobile apps, digital platforms
30	e24	Switzerland	Finance	n. a.	n. a.	Startup	2007	Mobile apps, mobile payment
31	Endress + Hauser	Switzerland	Manufacturing	$ 2.509.359.750	13,299	Incumbent	n. a.	
32	Tencent	China	IT	$ 44.000.000.000	54,309	Incumbent	2003	Mobile apps, digital platforms
33	Card Union Technology Co., ltd	China	IT	n. a.	n. a.	Incumbent	2006	E-commerce, digital platforms
34	Card Union Technology Co., ltd	China	IT	n. a.	n. a.	Incumbent	2013	Mobile apps, digital platforms
35	Anonymous		Health	n. a.	n. a.	Incumbent	2011	Internet-of-Things
36	Wishberry	India	Finance	n. a.	n. a.	Startup	2012	Digital platforms
37	Apple	USA	IT	$ 265.595.000.000	132,000	Incumbent	2008	Mobile apps, digital platforms
38	Anonymous		Manufacturing	n. a.	n. a.	Incumbent	n. a.	Internet-of-Things, digital platforms, data analytics
39	Rubicon Global	USA	Services	$ 450.000.000	381	Startup	2008	Digital platforms
40	Mohawk	USA	Manufacturing	$ 300.000.000	550	Incumbent	2010	Cloud computing, digital platforms
41	GoGet	Australia	Mobility	n. a.		Startup	2006	Product-service-systems, digital platforms
42	IBM	USA	IT	$ 80.000.000.000	350,600	Incumbent	2003	Software technology
43	THA Group	USA	Health	n. a.	100	Incumbent	2001	Internet-of-Things
44	Business	Germany	Media	200.000.000 €	1000	Incumbent	n. a.	Digital platforms
45	Technology	Germany	Media	3.000.000.000 €	12,000	Incumbent	n. a.	Digital platforms
46	Games	Germany	Media	300.000.000,00 €	1500	Incumbent	n. a.	Digital platforms
47	Knowledge	Germany	Media	n. a.	70	Startup	n. a.	
48	Printing	Germany	Media	n. a.	20	Startup	n. a.	
49	Education	Germany	Media	n. a.	8	Startup	n. a.	

Appendix C. Case coding

See Tables C1-C2.

Table C1
Coding scheme.

		Category	Abbreviation	Code	Explanation
Sense: Antecedents	*Organizational antecedents*	*Business model limitations*	*BM limit*	1	BM is a limiting factor
				0	BM is not a limiting factor.
		Resource utilization	*Resource util.*	1	Existing resources are utilized.
				0	Existing resources are not utilized.
		Financial need	*Fin. Need*	1	The firm is facing a financial need.
				0	The firm is not facing a financial need.
	Environmental antecedents	*Competitive pressure*	*Comp. pressure*	1	Strong competitive pressure
				0	No particularly strong competitive pressure
		Customer need	*Cust. Need*	1	Changing customer needs must be addressed
				0	Changing customer needs do not need to be addressed in particular.
		Technology innovation	*Tech. innovation*	1	Capitalized on new technology
				0	Did not capitalize on new technology
Seize: Outcome		*BMI type*		1	Evolutionary business model innovation
				2	Adaptive business model innovation
				3	Focused business model innovation
				4	Complex business model innovation

Table C2
Case coding as input for the csQCA.

No	Case	Organizational antecedents			Environmental antecedents			Outcome
		BM limit.	Resource util.	Fin. need	Comp. pressure	Cust. need	Tech. innovation	BMI type
1	Progressive Corporation	0	1	0	0	0	1	1
2	China United Telecommunication Corporation	0	0	0	0	1	0	3
3	Anonymous (Ericsson)	0	0	0	1	0	1	2
4	Anonymous	0	0	1	0	0	0	3
5	Suning Appliance Company Limited	0	0	0	1	1	0	4
6	Uber	0	0	0	0	1	1	3
7	Edeka	0	0	0	0	0	1	1
8	100percent	1	0	0	0	0	0	3
9	Anonymous	0	1	0	0	1	1	3
10	Cyberlibris	0	0	0	0	1	0	1
11	Apple	0	1	0	1	1	0	2
12	Philips	0	0	0	0	1	0	4
13	Walmart	0	0	0	1	0	0	1
14	Donkey Republic	1	0	0	0	0	0	1
15	Salesforce	0	0	0	0	1	1	4
16	eBay (Kleinanzeigen)	0	0	1	1	0	0	1
17	Schindler	0	1	0	0	0	0	3
18	Lufthansa	0	1	1	1	0	0	1
19	DP World	0	1	0	0	0	0	1
20	Alibaba	0	1	0	0	1	1	4
21	Netflix	0	0	0	0	0	1	4
22	Spotify	0	0	0	0	0	1	2
23	Hilti	0	0	1	0	0	0	4
24	Dow Corning	0	0	1	0	1	0	3
25	Anonymous	0	0	0	1	0	1	2
26	Anonymous	1	0	0	1	0	0	2
27	RTL Television	0	0	0	1	1	0	2
28	Allianz Suisse	0	0	1	1	0	0	1
29	Daimler: Car2Go	1	0	0	0	1	0	4
30	e24	0	1	0	0	0	0	2
31	Endress + Hauser	0	0	0	0	1	1	4
32	Tencent	1	0	0	0	1	0	4
33	Card Union Technology Co., ltd	0	0	0	0	1	0	3
34	Card Union Technology Co., ltd	1	0	0	0	0	0	1
35	Anonymous	0	0	0	0	1	1	1
36	Wishberry	0	0	0	0	0	1	3
37	Apple	0	1	0	0	0	0	4
38	Anonymous	0	0	0	1	0	0	3
39	Rubicon Global	0	1	0	0	0	0	4
40	Mohawk	1	0	1	1	1	0	4
41	GoGet	1	0	0	0	0	0	1
42	IBM	0	1	0	0	0	1	1
43	THA Group	0	0	1	0	0	1	3
44	Business	1	1	0	0	1	0	1
45	Technology	0	1	0	0	1	1	2
46	Games	0	1	0	0	1	0	2
47	Knowledge	0	0	0	0	1	1	1
48	Printing	0	0	0	0	1	1	2
49	Education	0	1	0	0	1	1	3

Appendix D. Truth tables

Abbreviations used in the following tables:
See Tables D1-D4.

Table D1
The truth table for evolutionary BMI.

Cust. need	Fin. need	Resource util.	Tech. innovation	Comp. pressure	BM limit.	OUT	n	incl	cases
0	0	1	1	0	0	1	2	1.000	1,42
0	1	0	0	1	0	1	2	1.000	16,28
0	1	1	0	1	0	1	1	1.000	18
1	0	1	0	0	1	1	1	1.000	44
0	0	0	0	0	1	0	4	0.750	8,14,34,41
0	0	0	0	1	0	0	2	0.500	13,38
1	0	0	1	0	0	0	6	0.333	6,15,31,35,47,48
0	0	0	1	0	0	0	4	0.250	7,21,22,36
1	0	0	0	0	0	0	4	0.250	2,10,12,33
0	0	1	0	0	0	0	5	0.200	17,19,30,37,39
1	0	1	1	0	0	0	4	0.000	9,20,45,49
0	0	0	1	1	0	0	2	0.000	3,25
0	1	0	0	0	0	0	2	0.000	4,23
1	0	0	0	0	1	0	2	0.000	29,32
1	0	0	0	1	0	0	2	0.000	5,27
0	0	0	0	1	1	0	1	0.000	26
0	1	0	1	0	0	0	1	0.000	43
1	0	1	0	0	0	0	1	0.000	46
1	0	1	0	1	0	0	1	0.000	11
1	1	0	0	0	0	0	1	0.000	24
1	1	0	0	1	1	0	1	0.000	40

Table D2
The truth table for adaptive BMI.

Cust. need	Fin. need	Resource util.	Tech. innovation	Comp. pressure	BM limit.	OUT	n	incl	cases
0	0	0	1	1	0	1	2	1.000	3,25
0	0	0	0	1	1	1	1	1.000	26
1	0	1	0	0	0	1	1	1.000	46
1	0	1	0	1	0	1	1	1.000	11
1	0	0	0	1	0	0	2	0.500	5,27
0	0	0	1	0	0	0	4	0.250	7,21,22,36
1	0	1	1	0	0	0	4	0.250	9,20,45,49
0	0	1	0	0	0	0	5	0.200	17,19,30,37,39
1	0	0	1	0	0	0	6	0.167	6,15,31,35,47,48
0	0	0	0	0	1	0	4	0.000	8,14,34,41
1	0	0	0	0	0	0	4	0.000	2,10,12,33
0	0	0	0	1	0	0	2	0.000	13,38
0	0	1	1	0	0	0	2	0.000	1,42
0	1	0	0	0	0	0	2	0.000	4,23
0	1	0	0	1	0	0	2	0.000	16,28
1	0	0	0	0	1	0	2	0.000	29,32
0	1	0	1	0	0	0	1	0.000	43
0	1	1	0	1	0	0	1	0.000	18
1	0	1	0	0	1	0	1	0.000	44
1	1	0	0	0	0	0	1	0.000	24
1	1	0	0	1	1	0	1	0.000	40

Table D3
The truth table for focused BMI.

Cust. need	Fin. need	Resource util.	Tech. innovation	Comp. pressure	BM limit.	OUT	n	incl	cases
0	1	0	1	0	0	1	1	1.000	43
1	1	0	0	0	0	1	1	1.000	24
1	0	0	0	0	0	0	4	0.500	2,10,12,33
1	0	1	1	0	0	0	4	0.500	9,20,45,49
0	0	0	0	1	0	0	2	0.500	13,38
0	1	0	0	0	0	0	2	0.500	4,23
0	0	0	0	0	1	0	4	0.250	8,14,34,41
0	0	0	1	0	0	0	4	0.250	7,21,22,36
0	0	1	0	0	0	0	5	0.200	17,19,30,37,39
1	0	0	1	0	0	0	6	0.167	6,15,31,35,47,48
0	0	0	1	1	0	0	2	0.000	3,25
0	0	1	1	0	0	0	2	0.000	1,42
0	1	0	0	1	0	0	2	0.000	16,28

(*continued on next page*)

Table D3 (*continued*)

Cust. need	Fin. need	Resource util.	Tech. innovation	Comp. pressure	BM limit.	OUT	n	incl	cases
1	0	0	0	0	1	0	2	0.000	29,32
1	0	0	0	1	0	0	2	0.000	5,27
0	0	0	0	1	1	0	1	0.000	26
0	1	1	0	1	0	0	1	0.000	18
1	0	1	0	0	0	0	1	0.000	46
1	0	1	0	0	1	0	1	0.000	44
1	0	1	0	1	0	0	1	0.000	11
1	1	0	0	1	1	0	1	0.000	40

Table D4
The truth table for complex BMI.

Cust. need	Fin. need	Resource util.	Tech. innovation	Comp. pressure	BM limit.	OUT	n	incl	cases
1	0	0	0	0	1	1	2	1.000	29,32
1	1	0	0	1	1	1	1	1.000	40
0	1	0	0	0	0	0	2	0.500	4,23
1	0	0	0	1	0	0	2	0.500	5,27
0	0	1	0	0	0	0	5	0.400	17,19,30,37,39
1	0	0	1	0	0	0	6	0.333	6,15,31,35,47,48
0	0	0	1	0	0	0	4	0.250	7,21,22,36
1	0	0	0	0	0	0	4	0.250	2,10,12,33
1	0	1	1	0	0	0	4	0.250	9,20,45,49
0	0	0	0	0	1	0	4	0.000	8,14,34,41
0	0	0	0	1	0	0	2	0.000	13,38
0	0	0	1	1	0	0	2	0.000	3,25
0	0	1	1	0	0	0	2	0.000	1,42
0	1	0	0	1	0	0	2	0.000	16,28
0	0	0	0	1	1	0	1	0.000	26
0	1	0	1	0	0	0	1	0.000	43
0	1	1	0	1	0	0	1	0.000	18
1	0	1	0	0	0	0	1	0.000	46
1	0	1	0	0	1	0	1	0.000	44
1	0	1	0	1	0	0	1	0.000	11
1	1	0	0	0	0	0	1	0.000	24

Out	*Output value*	Indicates whether the configuration leads to the outcome (e.g., evolutionary BMI) and fulfills the defined threshold criteria
n	*Number of cases in configuration*	
incl	*Sufficiency inclusion score*	Equals consistency: the proportion of cases yielding the outcome represented by the configuration (Greckhamer et al., 2018)
cases	*Case ID*	Case identifier based on Table B-1

Outcome: BMI Type = Evolutionary.
Outcome: BMI Type = Adaptive.
Outcome: BMI Type = Focused.
Outcome: BMI Type = Complex.

Appendix E. Antecedents

See Table E1.

Table E1
Explanation of sensed antecedents.

		Category	Explanation
Sense: Antecedents	*Organizational antecedents*	*Business model limitations*	*Business model limitations* as an antecedent for change. This implies firms recognize that their business model was unsuitable for further growth or the future business environment. For example, firms noticed that their business model was copied by competitors, not scalable to international markets, or at risk of being depreciated.
		Resource utilization	Firms leveraged their specific capabilities and knowledge to exploit opportunities for a digital BMI. Drawing from the resource-based view of the firm Barney (2016), we named this antecedent *Resource utilization.* Whether a firm already possessed the resources, knowledge, or capabilities for the new business model, or whether they created, hired, or acquired them, we

(*continued on next page*)

Table E1 (*continued*)

	Category	Explanation
		separated this antecedent into *Consuming* and *Creating*. For example, Apple had strong hardware and software development capabilities before creating the iPod and iTunes. Nevertheless, one case ("Gaming") from Mezger (2014) actively sourced new employees to bring new knowledge and capabilities into the firm.
	Financial need	We observe three sub-categories for this antecedent. First, *decreasing profitability* was sensed, such as higher costs or lower prices that can cause financial trouble. Second, *stagnation* of sales and customer demand prevents firms from achieving strategic goals. Third, the top management can actively create antecedents, such as *financial goals* that aim to make the firms more profitable.
Environmental antecedents	*Competitive pressure*	*Competitive pressure* threatens a firm's business model. We observe incumbent firms competing to maximize their value capture or a sudden rise of competition caused by a new entrant or substitutional business model.
	Customer need	This behavior change can either be a changed, previously different need: for example, the need to have access to a car or computational resources everywhere and every time instead of owning the product. Or it can be a new, previously non-existent need. For example, the need to have informative or entertaining content available free of charge and mobile. While a *customer threat* puts a firm's business model at risk, a *customer opportunity* provides the chance to extend the business model to serve these customers.
	Technology innovation	New technology provides a way to rethink the firm's business model. For example, cloud computing-enabled business models provide hardware or software services on a usage basis.

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