As Much Art as Science - Examining the Realization of Business Models Driven by Machine Learning Through a Dynamic Capabilities Perspective

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AS MUCH ART AS SCIENCE – EXAMINING THE REALIZATION OF BUSINESS MODELS DRIVEN BY MACHINE LEARNING THROUGH A DYNAMIC CAPABILITIES PERSPECTIVE

Research Paper

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Abstract

Machine learning (ML) technologies open up enormous potential to be unlocked through entrepreneurial activities in organizations, causing countless novel business models with ML at their core to emerge in the market. As ML technologies differ significantly from other digital technologies both in their characteristics and their effect on organizations, little is currently known about the complexities of the realization process for business models driven by ML and why only some organizations execute it successfully. By building on a qualitative study grounded on cross-industry insights from 20 expert interviews, this paper contributes to a greater understanding of the realization process by identifying ML-specific complications, before aiming to determine the underlying reasons for successful business model realization. We adopt a dynamic capabilities perspective and conceptualize eleven microfoundations that explicate how organizations build, implement, and transform business models driven by ML.

Keywords: Machine Learning, Business Model Realization, Dynamic Capabilities.

1 Introduction

Machine learning (ML) unlocks possibilities to support or entirely automate processes within organizations (Jordan and Mitchell, 2015) and further provides powerful opportunities for entrepreneurship by enabling entirely new services and business models (Chalmers et al., 2021; Davenport et al., 2020). ML denotes a technology that can be utilized to create instances of artificial intelligence (AI) by allowing algorithms to learn patterns hidden within data and then make predictions for new data (Russell and Norvig, 2021; Brynjolfsson and Mitchell, 2017; Mitchell, 1997). The novel business models with ML at their core are distinct from other types of business models enabled by information technologies (IT), as recent literature shows that ML not only opens up new possibilities for value proposition, but potentially impacts the overall business logic (as we will further discuss), e.g., by continuously learning with new data (e.g., Weber et al., 2022; Vetter et al., 2022). However, these studies have mostly examined the ideation of ML-driven business models, disregarding how organizations develop and realize them. Only little research extends beyond the ideation phase and covers the realization process of the broader category of business models enabled by data, focusing either on models of the development process (e.g., Hunke et al., 2017) or on the resources that are required for it (e.g., Lange et al., 2021). However, in fast-moving business environments, organizations need more than the ownership of expertise, processes, and resources to maintain sustainable competitive advantage (Teece, 2007). For instance, they must field a strategy that allows them to both defend their
position in the market against competitors and contingencies (Casadesus-Masanell and Ricart, 2011). Following Teece (2018), we argue that an organization’s dynamic capabilities allow it to connect strategy and business models to navigate complex and fast-changing environments through the creation, realization, and refinement of business models (Teece, 2018; Winter, 2003); a process that is “as much art as science” (Schoemaker et al., 2018, p. 27). Complicating development of suitable business models further, ML exhibits some characteristics that differ significantly from other digital technologies and come interleaved with distinct managerial challenges within organizations (Benbya et al., 2021; Berente et al., 2021), e.g., due to their ability to supersede humans at work (Murray et al., 2020). Moreover, the development of ML is highly uncertain and experimental in character (Choudhury et al., 2021; Amershi et al., 2019). This is problematic as organizations failing to counteract ML-specific challenges while navigating dynamic business environments may fail to acquire and maintain competitive advantages. We thus deem dynamic capabilities a suitable lens to examine the realization process of business models driven by ML and pose the following research question:

**How do organizations build dynamic capabilities to empower their ML-driven business model realization process?**

To answer this question, we conduct an explorative study and investigate the microfoundations that substantiate the dynamic capabilities enabling the realization of business models shaped by ML. In doing so, we contribute to extant dynamic capability literature in the context of digitalization by verifying and expanding known microfoundations with ML-specific aspects and identifying new microfoundations emerging due to unique ML characteristics. Furthermore, by specifying these ML-specific dynamic capability microfoundations, we open up the field for future organizational research on entrepreneurial activities to capture value from ML technologies. Additionally, we inform practitioners on the effect of ML technologies on the organization and its business environment during business model realization and offer guidelines for practitioners on how to create dynamic capabilities that aid the ML-driven business model realization process. Thereby, we support organizations in analyzing their present business model realization efforts and in building capabilities for future endeavors.

## 2 Theoretical Background

Next, we first present research on the development of business models with ML technologies at their core before covering the theoretical foundation of dynamic capabilities in the business model context.

### 2.1 Realizing ML-driven business models

Researchers have put great emphasis on examining the business model concept, which depicts the business logic of an organization, including how it creates and delivers value to its clients, as well as the corresponding architecture of revenue, costs, and profits (Teece, 2010). Numerous definitions of the term exist in the literature (Al-Debei and Avison, 2010; Wirtz et al., 2016; Zott et al., 2011; Birkinshaw and Ansari, 2015), of which we adhere to the definition by Osterwalder and Pigneur (2010, p.14) for this study, which reads as follows: “A business model describes the rationale of how an organization creates, delivers, and captures value.” The available conceptualizations of business models often consist of their constituting components, such as the value proposition or the revenue stream (e.g., Al-Debei and Avison, 2010; Zott and Amit, 2010; Remane et al., 2016). In information systems (IS) research, the business model is regarded as the missing link, acting as an intermediary between strategy, processes, and IT (Veit et al., 2014). Furthermore, the concept is seen as a useful lens for examining competitive advantage in management literature and is thus valuable in theory building to generate novel insights (e.g., Lanzolla and Markides, 2021; Prescott and Filatotchev, 2021).

AI, which denotes “the science and engineering of making intelligent machines” (McCarthy, 2007, p. 2), enables organizations to leverage additional potential in the context of digitalization (Davenport et al., 2020; Dingli et al., 2021; Makridakis, 2017). With the large availability of data and advancements in data analytics, AI technologies have thus regained importance in recent years (Agerfalk, 2020; Berente et al., 2021). As most modern AI systems have ML technologies at their core (Brynjolfsson and
Mitchell, 2017; Jordan and Mitchell, 2015), we use the term *ML* to refer to ML-based instances of AI in this study for terminological clarity. While the unique opportunities unlocked by ML drive the development of new types of business models in organizations (Weber et al., 2022; Vetter et al., 2022; Wamba-Taguimdjé et al., 2020), ML technologies also exhibit characteristics that differ considerably from other digital technologies, presenting ML-utilizing organizations with novel challenges (Benbya et al., 2021; Berente et al., 2021). First, the self-learning algorithms utilized in ML to learn and improve automatically from data (Amershi et al., 2019; Russel and Norvig, 2021) are incapable of reacting to environment states which they have not been trained with (Dennett, 2006) and require human guidance for framing the respective tasks and interpreting the results (Seidel et al., 2020; Salovaara et al., 2019). Second, ML systems can act autonomously (Berente et al., 2021; Baird and Maruping, 2021) and can even take over tasks previously firmly in human grasp (Schuetz and Venkatesh, 2020; Benbya et al., 2021). Lastly, modern ML systems have become increasingly complex, thus making their behavior inscrutable and difficult to understand for humans (Faraj et al., 2018; Asatiani et al., 2021). This is especially problematic as their introduction in organizations can create unexpected and unintended outcomes (Benbya et al., 2020; Benbya et al., 2021) that can lead to a variety of ethical issues, e.g., discriminating ML systems which include inappropriate factors in their decision-making (Martin, 2019). With the behavior of many ML systems being inscrutable for humans, preventing such unforeseen ethical, legal and practical consequences proves difficult (Asatiani et al., 2021). Investigating how this variety of unique challenges affects the business model development process is thus part of this study.

In light of the ongoing digitalization, IS researchers often utilize the business model concept to examine how advancements in IT, such as progress in big data and data analysis technologies, transform how established organizations create value and which novel types of ventures they enable (e.g., Hartmann et al., 2016; Steininger, 2019). For this study, we follow previous research and denote such business models as data-driven when they utilize data as a key resource (Hartmann et al., 2016). A subset of data-driven business models are ML-driven business models, which have infused at least one of their business model components with ML technologies (Vetter et al., 2022; Hahn et al., 2020). IS literature has thus far focused on the ideation of data-driven business models, largely disregarding how organizations develop and realize such business models and which strategies they employ (Lange et al., 2021; Wiener et al., 2020). Hunke et al. (2017) propose an innovation process depicting the major phases organizations must go through when developing data-driven business models and the tasks they must perform in each phase. Rashed and Drews (2021) differentiate the realization process into four pathways that established enterprises can take, depending on their data understanding and incentive for change, and elaborate corresponding implementation strategies. Similarly, Shollo et al. (2022) specify three ML value creation mechanisms through which organizations can reach their own organizational goals and present resources and conditions that must be met to shift between mechanisms. Finally, Lange et al. (2021) adopt the resource-based view of the firm (see Barney, 1991) and present the resources necessary for different phases of the business model realization process, which they subsume under four capabilities, along with challenges and enablers to fully utilize the organization’s resources.

### 2.2 Dynamic capabilities for digitalization

However, assembling the resources and capabilities needed to achieve sustainable competitive advantage is only one part of business model development (Teece, 2018). While these operational, ordinary capabilities aid organizations in operating a business model efficiently, e.g., in following a specified manufacturing program, an organization’s overlying dynamic capabilities determine the success in creating, implementing, and transforming business models (Teece, 2018; Winter, 2003; Ricciardi et al., 2016). In their seminal paper, Teece et al. (1997, p.516) define dynamic capabilities as the “ability to integrate, build, and reconfigure internal and external competencies to address rapidly-changing environments.” While early dynamic capabilities research disputed whether they are indeed firm-specific as proposed by Teece et al. (1997) or common among organizations and whether they necessarily confer superior performance (e.g., Eisenhardt and Martin, 2000; Peteraf et al., 2013), recent literature proposes that dynamic capabilities may consist of both elements that are common across
organizations and aspects that are idiosyncratic (Barreto, 2010; Yeow et al., 2018). We follow Yeow et al. (2018) in conceptualizing dynamic capabilities as both broad organizational capabilities and specific actions and in adopting, at the broad level, the three dynamic capability clusters, or higher-order capabilities, proposed by Teece (2007): sensing, seizing, and transforming (Teece, 2018). Each of the higher-order dynamic capabilities can be disaggregated into various second-order dynamic capabilities, or microfoundations (Teece, 2018), which represent the actions and processes enacted by individuals (including managers) within the organization, that build and maintain dynamic capabilities (Vial, 2019; Helfat and Peteraf, 2015; Yeow et al., 2018). The strength of an organizations dynamic capabilities then determines how successfully it innovates and adapts to rapidly changing markets and technological progress (Di Stefano et al., 2014; Warner and Wäger, 2019; Eisenhardt and Martin, 2000). Due to the highly disruptive and fast-changing nature of the digitalization in general, dynamic capabilities are seen as a suitable theoretical foundation to examine the mechanisms that enable organizations to engage in digitalization (Warner and Wäger, 2019; Ellström et al., 2022; Vial, 2019). Currently, literature is thus calling for additional research on how organizations build dynamic capabilities to propel their digital transformation forward and which microfoundations exactly constitute these dynamic capabilities in practice (Vial, 2019). Furthermore, dynamic capabilities enable business models in the sense that they allow organizations to rapidly design, test, and revise novel and modified business models, while simultaneously being enhanced by the organizational flexibility allowed by the business model of the organization (Schoemaker et al., 2018; Teece, 2018), which is especially relevant for organizations operating in rapidly-changing, complex, and uncertain environments (Schoemaker et al., 2018). Given the disruptive potential of ML-driven business models in particular (Davenport et al., 2020; Chalmers et al., 2021; Townsend and Hunt, 2019), in combination with the unique managerial challenges posed by ML (see section 2.1), we argue that dynamic capabilities are therefore a compelling perspective for investigating the determinants of successful ML-driven business model realization. As the allocation of dynamic capabilities into the three clusters proposed by Teece (2007) is widely accepted in the literature (Ellström et al., 2022; Yeow et al., 2018; Warner and Wäger, 2019), we adopt it for this study and elaborate on the three groups in the context of realizing ML-driven business models in the following.

Sensing is the “identification, development, codevelopment, and assessment of technological opportunities in relationship to customer needs” (Teece, 2014, p. 332). Sensing and shaping opportunities, as well as threats, is done through activities involving scanning, creation, learning, and interpretive activities, which need to be embedded into suitable organizational routines (Teece, 2007). Organizations must be aware of the ecosystem surrounding them, including customer needs and technological possibilities, as well as the structural evolution of markets and likely competitor responses (Teece, 2007) to be able to manage market uncertainty and detect opportunities (Teece, 2009). This dynamic capability is especially relevant for organizations with digital technologies deeply embedded in their strategy (Yeow et al., 2018), as it enables recognizing and understanding unexpected trends in fast-changing environments to be able to adapt accordingly (Warner and Wäger, 2019).

Seizing denotes the “mobilization of resources to address needs and opportunities, and to capture value from doing so” (Teece, 2014, p. 332). Once an opportunity is sensed by an organization, it must be addressed through new products, processes, services, or a combination of these, to ensure the value capture through appropriate investments (Teece, 2007). As the outcomes of such investment decisions are often highly uncertain, organizations must develop strong decision-making and evaluation abilities that foster innovation (Teece, 2007). When incumbent organizations are introduced to new technologies, they often experience a gap between the configuration of ordinary capabilities present in their organization and the optimal configuration required to fully utilize the technology (Karimi and Walter, 2015), necessitating seizing capabilities to incorporate the technology into the organization to allow capturing value from corresponding opportunities (Ellström et al., 2022).

Transforming is the “continued renewal” (Teece, 2014, p. 332) of the organization’s business model along with its resource base. Organizations must retain their ability to reconfigure their assets and organizational structures as their size grows and market and technologies change to maintain evolutionary fitness and achieve sustained profitable growth (Teece, 2007). To sustain competitive
advantage in dynamic environments, established routines need to be revamped constantly, which involves top management leadership skills, business model redesigns, and potentially even organizational restructuring for radical innovations (Teece, 2007; Helfat et al., 2007). The transforming capability thus aids in aligning existing resources to new strategies as well as in building or accessing required new resources (Yeow et al., 2018). Consequently, with digital technologies and especially ML being relatively new and many organizations lacking the associated expertise and routines, transforming capabilities are crucial for organizations that pursue a strategy infused by these technologies and, therefore, must acquire the corresponding resources (Yeow et al., 2018; Rindova et al., 2016).

3 Methodology

To answer our research question, we carried out a qualitative expert interview study (Bogner et al., 2009; Gläser and Laudel, 2004). In contrast, some comparable studies on dynamic capabilities in established enterprises select case studies for their qualitative approach (e.g., Yeow et al., 2018, Mousavi et al., 2019), which allow for in-depth investigations of phenomena in few organizations that are exemplary for the respective topic (Sarker et al., 2012). However, as novel business models are volatile, their success difficult to determine in the first years, and their established processes and resources to draw data from typically scarce, we decided to rely on multiple perspectives on our topic stemming from various organizations. Therefore, we chose to conduct an expert interview study, a suitable approach for incorporating a wide range of expertise on ML-driven value creation (e.g., Lange et al., 2021, Shollo et al., 2022) and an appropriate method for illuminating areas of research that have not yet been thoroughly explored (Corbin and Strauss, 2015; Myers and Newman, 2007). For the interviews, we concentrated on experts from the fields of digital business and data science with insights into the technical aspects as well as the business aspects of realizing ML-driven business models. The experts were chosen from organizations of various sizes (including established enterprises and start-ups) and in different industries (including experts from consulting firms or accelerators with an overview of a wide range of client organizations) and recruited through LinkedIn and other networks. All selected organizations initiated ventures to realize their own ML-driven business models or advise their clients in respective endeavors.

<table>
<thead>
<tr>
<th>ID</th>
<th>Position</th>
<th>Experience</th>
<th>Industry</th>
<th>Size</th>
<th>Scope</th>
</tr>
</thead>
<tbody>
<tr>
<td>E01</td>
<td>Product Lead ML</td>
<td>8 yr.</td>
<td>IT Services</td>
<td>Large</td>
<td>Extension</td>
</tr>
<tr>
<td>E02</td>
<td>Co-Founder</td>
<td>3 yr.</td>
<td>Software</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E03</td>
<td>Managing Director</td>
<td>5 (12) yr.</td>
<td>IT Services</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E04</td>
<td>Co-Founder &amp; CEO</td>
<td>6 (10) yr.</td>
<td>IT Consulting</td>
<td>Small</td>
<td>Flexible</td>
</tr>
<tr>
<td>E05</td>
<td>Global Head of ML</td>
<td>6 (17) yr.</td>
<td>IT Services</td>
<td>Very large</td>
<td>Extension</td>
</tr>
<tr>
<td>E06</td>
<td>ML Consultant</td>
<td>2 (5) yr.</td>
<td>IT Consulting</td>
<td>Small</td>
<td>Flexible</td>
</tr>
<tr>
<td>E07</td>
<td>Co-Founder &amp; Head of ML</td>
<td>5 yr.</td>
<td>IT Services</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E08</td>
<td>Co-Founder</td>
<td>5 (10) yr.</td>
<td>Software</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E09</td>
<td>ML Consultant</td>
<td>5 (7) yr.</td>
<td>ML Accelerator</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E10</td>
<td>Director of ML Strategy</td>
<td>6 (11) yr.</td>
<td>ML Initiative</td>
<td>Medium</td>
<td>Extension</td>
</tr>
<tr>
<td>E11</td>
<td>Lead ML Product Manager</td>
<td>6 (21) yr.</td>
<td>Software</td>
<td>Very large</td>
<td>Transformation</td>
</tr>
<tr>
<td>E12</td>
<td>Co-Founder &amp; CEO</td>
<td>2 yr.</td>
<td>IT Consulting</td>
<td>Small</td>
<td>Flexible</td>
</tr>
<tr>
<td>E13</td>
<td>Manager Digital CX</td>
<td>6 yr.</td>
<td>Technology</td>
<td>Very large</td>
<td>Transformation</td>
</tr>
<tr>
<td>E14</td>
<td>Senior Data Scientist</td>
<td>4 yr. &amp; 5 yr.</td>
<td>Consulting</td>
<td>Very large</td>
<td>Flexible</td>
</tr>
<tr>
<td>E15</td>
<td>Data Scientist</td>
<td>6 yr.</td>
<td>Automotive</td>
<td>Very large</td>
<td>Transformation</td>
</tr>
<tr>
<td>E16</td>
<td>Senior ML Consultant</td>
<td>3 yr.</td>
<td>Consulting</td>
<td>Very large</td>
<td>Flexible</td>
</tr>
<tr>
<td>E17</td>
<td>Senior ML Strategy Manager</td>
<td>4 (12) yr.</td>
<td>Consulting</td>
<td>Very large</td>
<td>Flexible</td>
</tr>
<tr>
<td>E18</td>
<td>Founder &amp; Managing Director</td>
<td>4 yr.</td>
<td>IT Services</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E19</td>
<td>Co-Founder &amp; CFO</td>
<td>3 (9) yr.</td>
<td>IT Services</td>
<td>Small</td>
<td>New Business</td>
</tr>
<tr>
<td>E20</td>
<td>Project Lead</td>
<td>6 yr.</td>
<td>ML Accelerator</td>
<td>Small</td>
<td>New Business</td>
</tr>
</tbody>
</table>

Notes: very large: empl. > 1000, large: empl. > 250, medium: empl. > 50, small: empl. ≤ 50

Table 1. List of interviewed experts.
In total, we conducted 20 expert interviews in the third and early fourth quarter of 2022. Table 1 shows a list of all interviewed experts, along with information on the corresponding organizations. Where applicable, we specified experience in time spent developing ML-driven business models and total time spent developing other types of digital business models in brackets, as ML-driven business models only recently gained popularity (Weber et al., 2022). Scope denotes whether the ML-driven business model was an entirely new, independent business model (New Business), developed out of an existing business model (Extension), or transformed from a previous business model (Transformation). The consulting firms in our sample mostly supported Transformation or Extension projects, yet could advise all scopes (Flexible). Interview E03 was conducted in person, and interview E17 over the phone, while all other expert interviews were held over the online conferencing tools Zoom or Microsoft Teams. All interviews lasted between 37 and 54 minutes with the exception of interview E03, which lasted 87 minutes due to the large amount of helpful anecdotes shared by the expert. The average duration of all interviews is 48 minutes. All expert interviews were either conducted in German or English. In preparation for the interviews, we created a semi-structured interview guideline (Myers and Newman, 2007). The interview guideline first contained introductory questions on the experiences of the interviewee and on the business models under study. It then progressed into thematic questions informed through extant research (Teece, 2007; Teece, 2018; Yeow et al., 2018; Warner and Wäger, 2019; Leemann and Kanbach, 2022; Lange et al., 2021), revolving around each of the three dynamic capability clusters for ML-driven business model realization. We recorded and fully transcribed all interviews. Next, we carried out a content analysis of the interview data based on the transcripts, choosing an inductive approach to avoid imposing preconceived ideas on dynamic capability theory on the data and instead let dynamic capability microfoundations emerge from the data (Hsieh and Shannon, 2005; Mayring, 2007; Myers, 1997). More specifically, we followed Gioia et al. (2013) in our coding process. To perform the coding, we used the MAXQDA software. We went through the transcripts line by line and assigned codes to sentences or parts of sentences that described the respective units, preferably in informant terms. Next, we iteratively grouped these emerging first-order concepts into meaningful second-order concepts, representing dynamic capability microfoundations. Finally, we assigned the latter to aggregate dimensions corresponding to the three dynamic capabilities clusters. During the analysis, we employed multi-researcher triangulation to achieve rigor and a high degree of objectivity (e.g., Hsieh and Shannon, 2005; Carter et al., 2014). In total, we identified three microfoundations of sensing, four of seizing, and four of transforming dynamic capabilities (see Figure 1). Furthermore, various factors uniquely complicating the development of ML-driven business models emerged from the data, which we grouped into two aggregate dimensions based on where they manifest. We thus identified four complexities taking effect within the business models themselves and three relating to dynamism in the organizations’ business environments, which we elaborate on in section 4.1.

4 Results

In the following, we first address particularities unique to ML-driven business models and their business environments that complicate business model realization and intensify the need for dynamic capabilities. Next, we elaborate on how the examined ML-driven organizations built and utilized their dynamic capabilities during business model development, using the tripartite clustering by Teece (2007).

4.1 Particularities of realizing ML-driven business models

The analysis of the interview data confirms that there are various aspects complicating the realization process of ML-driven business models, evoked by the ML technology at their core, which we subsume under the categories environmental dynamism and business model complexities.

Environmental dynamism delineates that both the technology of ML as well as the market surrounding corresponding business models are in constant flux. First, on the technological side, the speed at which new ML approaches are being developed is enormous (E11), even outpacing other digital technologies, according to the interviewees (E03, E18). Therefore, organizations and even start-ups that want to
position themselves in the field of ML must build competencies for research and development from the start to avoid getting left behind (E03). The rapid releases of novel ML services additionally demand much more flexibility from organizations during the development process of business models: “So these classic [business model] planning processes, that’s very difficult – that’s usually obsolete very quickly. The world changes too quickly” (E18). Second, the experts note that for many ML solutions, the respective market is still nascent (E08, E18), following the hype evoked by successful ML proof-of-concept projects (E20). As the market is currently developing, the IT infrastructure around ML systems is becoming increasingly modular and organizations are moving to specialize in application areas or ML components (E08, E11, E15, E18). “There will be companies that try and cover the full spectrum of the machine learning flow [for one specific application area] – or you’ll get companies that do best in breed on one specific component” (E08). Thereby, the ever-growing product portfolio of the large cloud service providers enables the purchase of specific components of ML development, such as computing power or pre-trained ML models, lowering the entry barriers for organizations with limited resources of their own at the cost of operating expenditure (E16). Third, as ML models absorb information about the organization’s environment in the form of data, changes in the business environment not only become problematic due to the possibly negative effects of the changes, but additionally due to their impact on the ML model within the organization’s ML system (E14, E16). When changes occur, the arising technical problems of data drift (new data is unlike training data of ML system) and concept drift (interrelations within new data is unlike interrelations in training data) must be addressed, which requires humans to interpret the data and evaluate whether the business idea remains relevant and which technical changes are necessary to ensure the ML system learns the desired patterns (E08, E14, E16).

**Business model complexities** denotes factors complicating business model realization from within the business model due to the unique effects of ML technologies. First, with ML being a general-purpose technology (see Brynjolfsson and McAfee, 2017), corresponding solutions can be utilized across various different sectors and business functions (E03, E05, E19). ML-developing organizations must thus be able to recognize application opportunities for their ML systems across industries and organizational boundaries (E03). Second, ML start-ups are often very tech-driven because of the high degree of required technical expertise in-house, frequently leading to some neglect of the business side (E09, E19). However, business expertise is elementary in developing business models, for instance, to quickly gather market feedback (E09). Additionally, ML solutions and their non-deterministic output require intensive engagement with the respective client to make them understand “how ML works and what they can do with it and where it really helps them” (E01), necessitating the building of expertise in sales and marketing (E01, E02). Third, while traditional digital solutions were separable into data and software, allowing the molding of standard processes into software (E10), that is no longer the case for ML approaches, in which data and software are inextricably connected (E08, E10, E12). This begets some technical challenges during development: Not only is data difficult and costly to acquire (E10, E12, E14, E17), but whether the process of abstracting information from data, storing it in an ML model, and then applying that in the real environment works and how well it works is difficult to ascertain in advance (E01, E07, E08, E10). Deploying an ML system to a new application area, therefore, not only requires retraining (E02, E10) but also extensive evaluation efforts (E06, E08, E10) that continue in the maintenance phase afterwards (E06). As one expert put it: “Mike Tyson said: ‘Everyone got a strategy until they get hit in the mouth.’ Your model is going to get hit in the mouth. What do you do with it when it does happen? How do you feed that into a system or [to] a person that can interpret that, update the model, get the new model, deploy it down so the next time it sees an exception, it can handle it?” (E08). The uncertain performance and the high retraining efforts when transferring ML systems between clients consequently make ML-driven business models very difficult to scale (E02, E07, E10). Fourth, ML systems have the capacity to highly individualize services to single end-consumers, e.g., in social media networks (E20), or to autonomously make high-impact decisions, e.g., in self-driving cars (E15). Coupled with their opacity (E15, E17), ML systems can cause more severe ethical ramifications than traditional software (E11, E14, E20). ML-driven organizations, therefore, need strong governance to foresee ethical issues early on when developing ML systems and to constantly review potential problems even after development to ensure operational safety (E14, E15) and data privacy (E11, E13, E15).
4.2 Dynamic capabilities for realizing ML-driven business models

In what follows, we present the identified microfoundations explicating how organizations successfully realize ML-driven business models despite the unique challenges described in section 4.1. Figure 1 gives an overview of the microfoundations that emerged from the data and the first order-concepts that informed them. Thereby, organizations first sense worthwhile opportunities via *sensing*, then design and commit to an appropriate business model via *seizing*, and lastly reconfigure the organization via *transforming* (Teece, 2018; see Warner and Wäger, 2019). While the dynamic capabilities are thus used sequentially when realizing a new business model, organizations must sense and seize opportunities continuously and transform parts of the organization periodically for long-lasting success, with stronger dynamic capabilities leading to faster and closer alignment to customer needs (Teece, 2018).

![Figure 1. Microfoundations of dynamic capabilities for realizing ML-driven business models emergent from the interview data.](image-url)
Sensing

Due to ML systems requiring large amounts of well-curated and current data, ML-driven business models can utilize their database to engage in data-driven sensing. By analyzing the available data manually or through automated processes, organizations can thereby gain insights into the characteristics and especially the needs of their customers (E01, E02, E05, E13, E16, E17). Through the organizations’ improved knowledge of their customers, they increase their capability for detecting opportunities to serve additional needs on the market. “[Name of former employer] always say that they get so much from data; they understand their target groups much better because they analyze massive amounts of data and, in fact, find many hidden fields” (E02). While the capacity for data-driven sensing is beneficial to various types of business models, “when you’re based around machine learning, [listening to data is] that much more important because that is driving how you win in the market. Also, your data is a form of stickiness with customers. I wouldn’t stop using Spotify because I feed it huge amounts of data, and the machine learning algorithm knows what to recommend” (E05). Another microfoundation of organizations’ sensing capability for ML-driven business model realization is reducing uncertainty inherent to ML development. Compared to traditional agile software development, where “you set an amount of story points or a certain view of what you’re going to do in the next sprint, and you know [...] what you will get at the end of that sprint. You don’t have that from the machine learning point of view because there’s data in the equation” (E05). Therefore, ML development requires prolonged experimentation phases to ascertain the possibilities of the envisaged ML solution (E01, E02, E05, E14, E18). Agile principles known from other digital products (E04, E16) such as small, incremental development steps (E03, E13, E16) while embracing a fail-fast mindset, quickly testing many ideas and allowing ideas based on mismatched assumptions to fail early (E07, E13), aid in reducing ML-induced uncertainty during development as well. Moreover, as setting up a functioning ML model is difficult early on (E09, E13, E17, E20), ML-driven business models often co-innovate, working closely with pilot customers to test assumptions early and to gain access to the customer’s data (E03, E06, E09). While this laborious experimentation phase is considerably longer still for problems that are not yet well-solved, these cases also yield the most interesting ML solutions (E04, E18). The last sensing microfoundation, simultaneous ML and business model experimentation, describes organizations remaining adaptable with their business model in parallel to their technical experimentation (E05, E09, E14, E18). First, organizations are well-advised to let the information derived from data also inform their business goals and to adapt their business model accordingly (E05, E19). “The data needs to guide you, and data is telling you about your business model and its effect in the market” (E05). Second, the question of which to develop first, business model or ML system, is “a bit of a hen and the egg question: [...] Do you first spend a lot of time in making a business model because that takes resources as well or do you make a proof of concept?” (E14). Waiting for the experimentation phase is often not an option either, as the organization must prove the rentability of the idea to justify the high costs of ML development (E02, E09, E11, E13). Organizations should therefore jump back and forth between the two, continuously evaluating the fit between their business model idea and the results of the ML experimentation process (E02, E12, E14, E20). Thereby, these two learning processes amplify each other, giving rise to positive synergies between them (E09, E14, E19): “Along the process, often you can find that you’re able to do more things. You’re able to actually predict some other things that you didn’t think about at the start” (E14). Due to the characteristic of ML being applicable across sectors and functions, organizations can thus “recognize that the tool we have created can do much more than what we have done with it so far” (E03). Organizations may find their solutions to be applicable in new, previously unaddressed sectors (E03, E19) or discover that their ML system intended for use by end consumers unlocks the potential to lower costs when used internally (E18). The reverse of the latter is even more common: “We develop something for a specific section in the value chain – for example, for production, error management processes is a big topic for us – and then we suddenly realize our application has a lot of potential to be used in after sales” (E18).
Seizing

Organizations seeking to capitalize on opportunities with their ML-driven business model realization process need the capacity to react to market or environment changes through continuous business model alignment. While all types of business models should be adapted regularly to reflect market conditions (E09, E11), being able to respond quickly to developments is especially critical for business models in rapidly changing markets such as the ML market (E03, E11). As dynamism in the market also enters ML products through data, causing data or concept drift, the need for continuous alignment is further exacerbated: “It starts with an invoice template, which changes in some country because some additional information is necessary, and I have to learn to extract that too if I want to extract something. [And it ends] with the fact that suddenly we have to keep a distance of 2 meters, we all have to wear masks, and the life behavior has completely changed, and therefore certain business processes have completely changed” (E11). To enable fast business model adaptations, organizations may establish departments such as innovation labs to rapidly test hypotheses and business ideas, while simultaneously anchoring the process of industrializing and scaling promising ideas within parts of the organization as well, e.g., in an ML factory unit (E17, E20). The potential ethical issues arising from some ML solutions demand additional awareness and that organizations are quick to respond to new regulations and to adapt their business processes accordingly in a responsible manner (E04, E05, E06), which can be fostered through involving people with differing perspectives (E06). Another microfoundation fueling the seizing capability of organizations realizing ML-driven business models is their ability for common knowledge building among departments due to three reasons: First, for the development process of ML systems to run smoothly, it needs the involvement of experts with different skillsets and perspectives, such as data engineers, ML engineers, sales experts, and domain experts (E17, E20). To allow experts from the business side to give input during development, organizations must ensure that all employees across organizational structures have some understanding of ML technologies and how they function (E01, E02, E08, E11, E14, E19). Second, that shared technical understanding is also necessary beyond ML development. As the output of ML models is non-deterministic and often uncertain in advance (E01, see section 4.1), ML-driven business models need highly tech-savvy sales experts to be able to explain the unique characteristics as well as their ramifications to clients (E02, E08, E11, E20). Such skilled sales also “have to be able to transport […] trust in the technology, because that has not been there until today” (E11). Third, a shared technical understanding sharpens the senses of all members of an organization for ML-specific issues (E10, E14, E18). Decisions made around a deployed ML system can unintentionally alter its results, e.g., in the visual inspection example of an expert, where “someone says 'Hey, we’re going to install new lights’ or some other stuff, which at first has no direct dependency, but of course then maybe the image is influenced and then all of a sudden my model no longer works” (E10). As ML systems can not interpret their surroundings (see section 4.1), the humans around them must thus possess an awareness of such issues and the technical understanding for reasonable interpretations and for requesting intervention if necessary (E10, E14). Moreover, with more members of an organization paying attention to the potential within their data, detecting promising ML use cases and exploiting synergies in data silos across departments becomes significantly easier (E14). Next, the unique properties of ML solutions further demand that corresponding business models engage in ML-specific customer relationships. Due to the technology’s complexity and the potential impacts of ML adoption, like ML taking over creative tasks from humans, solutions must be marketed with some finesse, laying a focus on communicating the added value of solutions and addressing both budget owners as well as experts with technical understanding (E01, E03, E08). To better understand how to approach and work with their customers, many ML start-ups in the B2B sector start with a consulting-oriented business model before transforming to a product- or service-based model (E03, E07, E08, E10, E12, E19). This not only helps them learn from the clients’ business problems but also from their data to enable improvements to the ML system (E07, E10). The consulting model further alleviates marketing challenges caused by the uncertainty of ML project outcomes: “The problem with machine learning, the failure rate for machining applications is still 60-70%, somewhere there. That failure rate needs to come down to like 20%, and then enough companies will start adopting this on a scale that makes sense. And then once that happens, you will have people switch to understanding how to license the software and...
not need consultation behind it as well” (E08). Switching to product-based business models is aspired by many ML start-ups due to the higher scalability and disruptive potential (E08, E17, E20), whereby keeping the ML model hidden within the system a secret and only providing and selling its generated solutions is promising to be the “holy grail” (E17) of approaches, allowing for the best monetization (E08, E17). The fourth seizing microfoundation identified in the interviews is intensive partnerships & ecosystem play. For development partners of ML-driven business models to be willing to give out their sensitive data for the ML development process, mutual trust and strong contractual agreements must be in place (E01, E16). Customers only enter such partnerships “if they know you as a provider or find you reputable and [...] if they have sufficient need to do something in that area” (E01). Partnerships thus also help in knowing the customer and validating assumptions about the customer’s need (E01, E16). Furthermore, the high dynamism of the ML market coupled with the increasing modularity of cloud and ML services (see section 4.1) amplifies the benefits of strong collaboration and joint learning through ecosystem play, especially for small and medium-sized enterprises (E17, E18). Organizations should thus rather strive to “build up many solutions [in a network] and see the strengths of them than acquire everything [themselves], [having] to build up a huge body of knowledge over many years. So I think I have to develop the ability to enter into this collaboration and say that ‘he won’t take away my water, he can support me’ and then I think you have to develop these joint business models” (E18).

Transforming

As ML-developing organizations experience influences of the technology across all departments (E11, E18), reconfiguring their structure towards organizational structures enabling ML innovation unlocks the full potential of ML. When developing novel ML business models within the organization, centralized teams are no longer recommended due to the resulting gap between domain experts and the ML team (E07, E16, E18). More suitable configurations include the hub-and-spoke model, which pools ML expertise in a hub that closely cooperates with experts throughout the organization that are close to the business side and endowed with technical understanding (E05, E07, E16, E18). For some established organizations, however, realizing an ML-driven business model that cannibalizes their own business can prove unsustainable within their company boundaries (E04, E05, E17). For example, “lawyers sell hours. No lawyer in the world wants to become more efficient; that’s the last thing he wants” (E04). To circumvent this issue, such organizations may pursue corporate spin-offs to capture new parts of the market (E04, E05, E17). “We are working with an insurer at the moment who’s been around for hundreds of years as a company, and they’re creating a new business which will be the claims experience itself which will be entirely driven by machine learning. [...] So, what they’ve done with that model is they’ve created a separate company, and they will eventually move out of the insurer, and they funded that company themselves. So, the insurer will still be a majority stakeholder, but they recognized that they couldn’t create such a different business model within an old insurance business model” (E05). This approach further helps in attracting talent as well as novel partnerships, maybe even with former competitors (E17), but also represents a large investment that takes a long time, “about three to five years” (E05), to pay off. Nevertheless, the experts advise highly disruptive business models: “If [the ML-driven business model] becomes fundamental like that, spin it off” (E04). Besides appropriate structures, ML-driven business model realization further benefits from organizational culture fostering ML innovation. While concerns often emerge when adopting novel technologies, especially ML-driven business models are often met with resistances (E06, E14, E16) due to their unique implications for humans at work (see section 2.1). Realizing ML-driven business models, however, calls for an organizational culture fostering curiosity and “willingness to embrace change, to accept what makes ML solutions very different than other ones, which is the amount of uncertainty that [they] might imply. [...] There needs to be awareness also of the risks that [uncertainty] might imply” (E06). Members of the organization should be willing to take risks, accepting of failure, and championing trial-and-error approaches (E02, E05, E11, E13, E15, E17, E18). Building such a culture further sensitizes members of all departments for added value in data (E17) but may call for extensive change management efforts in established enterprises (E06). Another microfoundation of the transforming capability is the top management commitment. As the realization of ML-driven business models must be carried by all parts of an organization, committing to and communicating its strategic importance from the top management
is crucial (E06, E13, E14, E16, E17). This is especially important in traditional organizations like “insurance companies, for example: They don’t have any pressure to change at the moment. Business is good. They have nice margins on their traditional insurance policies. […] Of course, there are a few fintech players who are just starting to act in a more innovative, faster, and more customer-centric way. But the pressure from outside has not yet been felt. That means there has to be an internal, intrinsic motivation to develop new business models, and there has to be oomph behind it from the board” (E17). Furthermore, the top management must secure the budget for ML development (E01, E02, E06, E13), which is both costly (E06, E09, E11) as well as risky due to the outcome being uncertain (E09, E18). Thereby, laying a large focus on performance indicators and costs “destroys the innovation” (E13). Having top managers that understand the need for extensive and untied experimentation during ML development and provide the necessary budget thus benefits the business model realization (E06, E11, E13, E14, E18). Lastly, the microfoundation cross-industry knowledge acquisition describes an organization’s ability to gather insights through its network of partners. Due to ML being a general-purpose technology, these insights are not necessarily limited to the organization’s market, which makes the exchange with partners equipped with vast experience on different ML projects, such as consulting firms, very attractive (E05, E16, E17). Such exchange is fostered through strong internal champions who understand ML technologies and are driven to motivate for novel ML business ideas (E04, E06, E07, E19). Additionally, as the ML market is relatively new and changes within it can be far-reaching (see section 4.1), e.g., due to new regulations, networking with the ML community and the scientific field is essential for maintaining competitive advantages (E02, E09).

5 Discussion

By adopting a dynamic capabilities perspective, we uncover the microfoundations that explain how organizations build the sensing, seizing, and transforming capabilities that empower them in realizing ML-driven business models. More specifically, we conceptualize three sensing, four seizing, and four transforming microfoundations (see Figure 1), answering our research question. Our study makes multiple theoretical contributions. First, motivated by scholars stating that organizations must build dynamic capabilities for digital transformation efforts (Warner and Wäger, 2019; Wamba et al., 2017; Shollo et al., 2022; Mikalef et al., 2020) and to confront turbulent environments (Wilden and Gudergan, 2015), we contextualize and verify the suitability of the dynamic capabilities perspective for the realization of ML-driven business models. Second, with dynamic capabilities playing a large role in the success of organizations realizing business models (see Teece, 2018; Winter, 2003; Ricciardi et al., 2016), we illuminate the processes and practices underlying the dynamic capabilities of these organizations. More specifically, we theorize on microfoundations on which ML-specific dynamic capabilities are grounded, answering a call for research on dynamic capabilities for digitalization (Vial, 2019). Thereby, we extend extant research on realizing data-driven business models revolving around models of the development process (e.g., Shollo et al., 2022; Rashed and Drews, 2021; Hunke et al., 2017) and the necessary resources and ordinary capabilities (e.g., Lange et al., 2021) by delineating how organizations build the ML-specific dynamic capabilities that enable them to orchestrate their resources in the realization process for sustainable success (see Teece, 2018). Third, we corroborate and expand the results of previous research stating that experimenting with business model ideas helps organizations reduce uncertainty (Andries et al., 2013). While organizations creating value from other digital technologies can tinker with novel business model ideas at very low costs (Huang et al., 2017; Lange et al., 2021), the development of ML technologies requires high up-front investments. Our results thus suggest that experimentation for the two development processes, ML development and business model development, must be interleaved to reduce the associated uncertainties simultaneously. Fourth, our results contribute to research building on the dynamic capabilities perspective in several ways. Our identified microfoundation of data-driven sensing gives support to recent literature reporting that organizations must increasingly digitize their sensing capabilities to quickly understand changes in highly dynamic markets (Nambisan et al., 2017; Warner and Wäger, 2019). The identified seizing microfoundation continuous business model alignment further
underscores research emphasizing the need for rapid strategic realignment in such markets characterized by high velocity and uncertainty (Teece et al., 2016; Peteraf et al., 2013). Additionally, while the benefit of collaboration in inter-organizational networks to innovation has been shown in the literature (e.g., Schilling and Phelps, 2007), our results suggest an exacerbated need for ecosystem play in the ML market due to its increasing modularity and partnerships involving the exchange of data requiring high mutual trust between partners. Regarding transforming microfoundations, ML-driven business models need the involvement of all members of the organization as per our results and thus necessitate an organizational culture that emphasizes openness to change, cross-departmental collaboration, and sensitizes towards ML- and data-specific topics. These findings coincide with literature on digitalization efforts, which similarly require change management efforts to overcome resistances to change (Singh and Hess, 2017; Ellström et al., 2022; Warner and Wäger, 2019). Lastly, while many types of digital business ideas benefit from the agility offered by developing the new business model next to traditional structures in a bimodal organizational structure (Haffke et al., 2017; Lange et al., 2021), we found that the increased capacity of ML-driven business models to cannibalize an organization’s own business may more often demand realization outside of previous organizational boundaries. Furthermore, our study makes two major practical contributions. First, we guide organizations by conceptualizing the novel challenges that arise when realizing business ideas driven by ML technologies. Practitioners can thus circumvent these issues and their implications when designing their business model realization process. Second, practitioners can utilize the presented microfoundations as guidelines on how to build dynamic capabilities that empower ML-driven business model realization processes. We thereby enable decision-makers to identify and make the necessary changes within their organization to align it for optimal capacity to realize ML-driven business models.

Our study is subject to limitations that invite future research. As our focus lay on capturing a practitioner’s perspective, we utilized the broad scope of our qualitative study to identify microfoundations grounded on expertise on a variety of business model realization cases. Yet, this leaves the quantitative measurement of the microfoundations’ effectivity in building dynamic capabilities or the associated success of business model realization endeavors unresolved to date; a limitation shared by comparable research on dynamic capabilities (see Warner and Wäger, 2019; Mousavi et al., 2019). Future research could therefore operationalize our microfoundations to both verify them and measure their effects in real-time longitudinal studies. Particularly their impact on the speed and degree of an organization’s alignment to customer needs (see Teece, 2018) during different phases of the realization process could thereby be of interest. Moreover, future research might investigate whether involving consultants in the realization process of business models alters how dynamic capabilities are built. To further expand on this work, future research could examine the interaction of ordinary capabilities (see Lange et al., 2021) and dynamic capabilities during business model realization.

6 Conclusion

In summary, our study represents a first step in examining how organizations navigate the ML-driven business model realization process despite ML-specific complications. Based on data from 20 expert interviews with practitioners, we thus shed light on the dynamic capabilities that empower organizations in realizing ML-driven business models. As results, we conceptualize various microfoundations (see Figure 1) on which these dynamic capabilities are grounded and that are crucial for counteracting the identified ML-induced complications in the business environment and the business model itself. Yet, further research is needed to unpack the full potential of ML-driven business models.

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