Understanding dynamic capabilities in emerging technology markets: antecedents, sequential nature, and impact on innovation performance in the extended reality industry

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Abstract
Purpose – The purpose of this study is to empirically investigate the role of dynamic capabilities, specifically the sequence of sensing, seizing, and transforming capabilities, in highly uncertain, emerging technology environments. Focusing on the extended reality industry, the study aims to understand the antecedents to these dynamic capabilities, their sequential nature, and their subsequent impact on innovation and company performance.

Design/methodology/approach – Based on a survey of 130 German companies in the extended reality sector, we built a structural equation model that explores the relationship between dynamic capabilities, their antecedents, and their effect on innovation and company performance.

Findings – The analysis suggests that sensing capabilities positively influence seizing and transforming capabilities, while seizing directly contributes to transforming. Transforming capabilities are linked to improved innovation performance, which in turn boosts company performance. Organizational ambidexterity, market orientation, and technology orientation are found to be crucial antecedents, accounting for 33.1% of the variance in sensing capabilities.

Originality/value – This research illuminates the interdependence of dynamic capabilities in highly uncertain business environments, such as emerging technology markets. It contributes original insights by elucidating the sequential nature of dynamic capabilities and identifying their vital antecedents. It also enlarges the understanding of how dynamic capabilities impact firms’ innovation performance.

Keywords Dynamic capabilities, Innovation performance, Virtual reality, Market orientation, Technology orientation, Organizational ambidexterity

1. Introduction
Dynamic capabilities (DCs) describe a company’s ability to continuously adapt and change its resource base in response to market changes, customer demands, and new technologies (Baía and Ferreira, 2019; Schoemaker et al., 2018; Teece, 2007; Teece et al., 1997). These capabilities enable organizations to remain competitive and respond to new opportunities and challenges (Gelhard and von Delft, 2016; Helfat and Raubitschek, 2018). DCs are frequently linked to the innovation performance of a company, consequently leading to better company performance in general (Farzaneh et al., 2021; Ilmudeen et al., 2021; Robertson et al., 2021;
Companies that know how to leverage DCs are also more likely to outperform competitors (Correia et al., 2021; Robertson et al., 2021).

DCs are particularly important in emerging technology markets, for which business models are still being developed and best practices often do not yet exist (Linde et al., 2021; McLaughlin, 2017; Schoemaker et al., 2018): “Large disruptive events such as the introduction of a radically new technology [...] or of drastic changes in market segments or preferences [...] will also spur firms’ efforts to develop and utilize dynamic capabilities to transform or reconfigure their substantive capabilities” (Zahra et al., 2006, p. 931). At the same time, such uncertain environments make the routinization of knowledge acquisition and resource expansion even more difficult (Helfat and Raubitschek, 2018; Linde et al., 2021; Mikalef and Pateli, 2016).

This research paper focuses on the extended reality (XR) industry as a highly relevant case of emerging technologies, as explored by Halaweh (2019) and Sieβ et al. (2017). XR encompasses virtual reality (VR), mixed reality (MR), and augmented reality (AR) technologies that provide users with immersive experiences beyond the confines of the physical world. It comprises not only the internal employment of enabling frameworks and applications, it also includes the creation and dissemination of content utilizing underlying technologies (Müttterlein and Hess, 2017). Most recently, XR has received increased scholarly attention as one of the base technologies required for the metaverse (Ball, 2021; Narin, 2021; Park and Kim, 2022). However, the industry is still relatively small and XR devices have not yet reached high market penetration. Since the underlying technologies are rapidly evolving (Zabel and Telkmann, 2022), it can thus be considered a typical example of an emerging technology environment.

For the analysis, the paper builds upon Teece’s (2007) influential conceptualization of DCs as a tripartite division into sensing, seizing, and transforming capabilities. However, it is noteworthy that Teece originally preferred the term ‘reconfiguring’ to ‘transforming’ in his seminal work on DCs (Teece, 2007; Teece et al., 1997). Nevertheless, later research used both terms interchangeably or focused on ‘transforming’ (Teece, 2018a). We also use both terms interchangeably, while we focus on the updated concept of ‘transforming’.

The tripartite of sensing, seizing, and transforming explains how companies navigate constantly changing environments by identifying, adapting, and routinizing in light of new opportunities (Schoemaker et al., 2018; Schilke et al., 2018; Maijanen and Jantunen, 2016; Teece, 2018b). The three dimensions of DCs are closely interrelated and reinforce one another. In uncertain environments, sensing capabilities are found to be particularly important and may enable the development of seizing capabilities, for example by enabling companies to quickly prototype and launch new products or services in response to market demands (Zabel et al., 2023). However, without effective transforming capabilities, firms may struggle to effectively coordinate and align these changes across their various business functions and activities (Jantunen et al., 2012; Makkonen et al., 2014). DCs may therefore be procedurally linked as proposed by Teece (2007), studies also have conceptualized them with side-by-side (Farzaneh et al., 2021; Feiler and Teece, 2014; Ilmudeen et al., 2021) and circular relationships (Aramand and Valliere, 2012; Weaven et al., 2021). Also, empirical findings are contradictory with regard to which elements of Teece’s conceptualization directly affect innovation performance (Gelhard and von Delft, 2016; see also Cordero Páez et al., 2022; Naldi et al., 2014).

In addition, antecedents contribute to the development of DCs. The most prominent concepts include market orientation and technology orientation. The emphasized proximity to markets and technological developments has been considered an antecedent of DCs, contributing positively to a renewal of the resource base through DCs (Correia et al., 2021, 2022; Najib et al., 2017; Rezazadeh et al., 2016). Market orientation refers to a firm’s focus on understanding and responding to the needs and preferences of customers. It involves more or
less dedicated resources for gathering and analysing customer feedback and using this information to drive decision-making. Technology orientation, on the other hand, refers to a company’s focus on developing and applying new technologies to drive innovation. Due to their strong market and technology orientation, they are better able to understand and respond to market changes and customer demands. In addition, the balancing between explorative and exploitative innovation activities has been proven to affect DCs (Birkinshaw et al., 2016; Jurksiene and Pundziene, 2016; van Lieshout et al., 2021; Zimmermann and Birkinshaw, 2016).

In our study, we focus on DCs as a logical sequence of distinct activities, analysing their impact on innovation and (in turn) on competitive performance. Furthermore, we extend the DC framework by also including antecedents of dynamic sensing capabilities (DSCs) such as tech orientation, market orientation, and organizational ambidexterity, which serve as a starting point of the DC chain. To do so, the present study gathers data from a representative sample of 130 XR companies in Germany. We analysed the data via a structural equation model in SmartPLS.

The present study underscores the foundational role of DSCs for firms operating in emerging technology environments. Building on this, it contributes to the ongoing debate on the sequential nature of DCs (Robertson et al., 2021; Weaven et al., 2021) by underscoring the up-/downstream nature of DCs. Contrary to previous research (on presumably less dynamic technology environments), only transforming capabilities significantly affect innovation performance, further underscoring the step-by-step nature of DCs in emerging technology environments. Regarding antecedents of the crucial sensing capabilities (as the starting point of the ‘DC chain’), our study highlights the relevance of a balance between market and technology orientation, as well as the need for organizational ambidexterity, catering to both incremental and radical innovation.

2. Theoretical background
The literature on DCs is extensive and wide-ranging. As Kump et al. (2018) point out, “the role of DC is to modify a firm’s existing resource base and to transform it intentionally and in alignment with strategic assumptions in such a way that a new bundle or configuration of organizational resources is created” (p. 1150). While DCs have been defined in various ways, two broadly differentiating theoretical streams emerged. The first view is oriented towards Teece (2007), the second towards Eisenhardt and Martin (2000). The first view is rather broad and contains abstract conceptualization of capabilities on capabilities, i.e. the seminal tripartite of “generic micro-foundations” (Kump et al., 2018, p. 6) sensing, seizing, and transforming.

In the second view, following Eisenhardt and Martin (2000), much more specific functional capabilities can be identified, for example, product development routines or strategic decision-making routines. Following this view, other examples are absorptive, integrative, and innovation capabilities (Hou, 2008); learning, integration, and coordination capabilities (Pavlou and El Sawy, 2011); and knowledge acquisition, generation, and combination capabilities (Zheng et al., 2011).

While recent research argues for a reconvergence of those streams (Wilden et al., 2016), those streams still impact the theoretical foundations of DCs (Peteraf et al., 2013). The intrinsic merits of the ‘capability on capability’ stream are particularly relevant in the context of our study. To begin with, while the other dynamic capability conceptualization is strongly domain-dependent or “specific” (Baía and Ferreira, 2019), the first stream offers a comprehensive, generalized approach. This view is particularly apt when dealing with highly dynamic and uncertain environments, where it is unclear which ‘specific’ dynamic capabilities may be crucial. This certainly applies to the XR industry, which is not only
The most prominent approach (Schilke et al., 2018) is Teece’s (2007) original tripartite of sensing, seizing, and transforming capabilities, which aims to define firm DCs. As the originator of the dynamic capabilities concept, Teece’s original tripartite inherently encapsulates the foundational essence of the idea, namely coping with emerging, dynamic situations with the potential for radical innovation and profiting from those innovations (Chiu et al., 2016; Teece, 2018b). His model is also useful when analysing digital business ecosystems (DBEs) (Maijanen, 2022). In the context of emerging technologies, where DBEs play a pivotal role, Teece’s framework harmonizes with the nuanced requirements of orchestrating and complementor firms within these ecosystems (Linde et al., 2021; Zabel et al., 2023).

In his model, sensing describes the ability of a company to identify and understand changes and trends in the market, including customer preferences and competitors’ actions. This involves collecting and analysing data in various ways, in order to understand customers, market trends, and technological advancements. The acquired knowledge is brought together and synthesized in one company, offering companies opportunities to identify needs for innovation (Farzaneh et al., 2021; Ilmudeen et al., 2021; Pundziene et al., 2022; Robertson et al., 2021; Teece, 2018b; Xin, 2018).

Seizing is the ability of a company to take advantage of opportunities that have been identified through sensing (Aramand and Valliere, 2012; Feiler and Teece, 2014; Khan et al., 2020). This involves developing and implementing specific routines and practices that allow the company to capitalize on the identified opportunities (Linde et al., 2021; Teece, 2007). Seizing also involves managing and coordinating the resources at hand, such as employees and their skills, technologies, and finances, to ensure that the company can take advantage of the identified opportunities. It is a known problem that some companies cannot properly transform their knowledge into innovation (Teece, 2018b).

Transforming refers to the ability of a company to adapt and change in the long term (Kump et al., 2018; Teece, 2007). This involves continuously improving and evolving the company’s processes, as well as developing and implementing new practices and structures to continuously harness existing resources (Zahra et al., 2006). For example, a company might have to restructure its organizational core, management, and practices, if developments such as artificial intelligence become essential (Lee et al., 2019). Transforming also instigates the implementation of new processes and nurturing of networks, and may result from interorganizational alliances or organizational-level group learning (Hamid Hawass, 2010), and may affect innovation especially for in the XR industry (Zabel and Telkmann, 2024).

Teece’s concept has been applied widely in academic research (Ellström et al., 2022; Kump et al., 2018), and numerous studies have investigated the effects of DCs on various aspects of business performance, including overall company performance (Laaksonen and Peltoniemi, 2018; Makkonen et al., 2014), broader strategic and business model performance (Gelhard and von Delft, 2016), and, most notably, innovation performance (Ghosh and Srivastava, 2022; Ilmudeen et al., 2021; Plättfaut et al., 2015; Pundziene et al., 2022; Zheng et al., 2011).

DCs have been shown to play an essential role in emerging technologies and market transformation (Baía and Ferreira, 2019; Konlechner et al., 2018; McLaughlin, 2017; Zahra et al., 2006). Scholars have demonstrated them to be closely related to successfully implementing and monetizing emerging technologies (McLaughlin, 2017) or to leveraging radical technological innovation (Chiu et al., 2016; Teece, 2018b). Furthermore, similar concepts, such as environmental dynamism (Girod and Whittington, 2017; Wilhelm et al., 2015) and market dynamism (Baía and Ferreira, 2019; Wang et al., 2007), are discussed as being central to DCs. However, while DCs are frequently conceptualized in light of radical
innovation and emerging technologies, most research does not empirically examine the relationship between the two. Moreover, emerging technologies are frequently organized around DBEs, which are signified by a central firm orchestrating the ecosystems and numerous complementor firms, each requiring different sets of DCs (Linde et al., 2021; Maijanen, 2022; Zabel et al., 2023).

2.1 The sequential nature of DCs
Teece proposed the three DCs as being interlinked, one leading to another (Teece, 2007). This idea has been discussed extensively in previous research (Aramand and Valliere, 2012; Feiler and Teece, 2014; Robertson et al., 2021; Weaven et al., 2021; see Table 1).

Studies exhibit a variety of relationship models, including interdependent/side-by-side (Feiler and Teece, 2014; Jantunen et al., 2012; Pundziene et al., 2022), or bi-directional/circular conceptualizations (Aramand and Valliere, 2012; Linde et al., 2021; Naldi et al., 2014; Weaven et al., 2021). Studies also analysed strictly linear sequences of DCs (Chiu et al., 2016; Zabel et al., 2023; Zheng et al., 2011) or ‘full’ one-directional sequences, where ‘earlier’ DCs may also affect more downstream DCs and ultimately the outcomes directly (Gelhard and von Delft, 2016; Maijanen and Jantunen, 2016; Robertson et al., 2021).

Building on Teece’s conceptualization and the rich literature that both point to the possible existence of ‘full’ one-directional sequences of DCs, we assume that the synchronous but ontologically and temporally upstream activities of sensing capabilities influence seizing and transforming capabilities, while seizing has a direct positive influence on transforming capabilities. As research hypotheses, we thus propose:

\[ H1a. \] Sensing capability has a direct positive effect on seizing capability.

\[ H1b. \] Sensing capability has a direct positive effect on transforming capability.

\[ H1c. \] Seizing capability has a direct positive effect on transforming capability.

2.2 Antecedents of dynamic sensing capabilities
Given the foundational role of DSCs in emerging technology environments – where they serve as the starting point of the DC sequence – it is particularly interesting to study the antecedents of this quintessential DC. Since sensing depends on the intake of market information as well as technological knowledge, a propensity of the firm towards one or the other may affect DSCs. In addition, the balancing of explorative and exploitative innovation activities in a rapidly evolving market where radical innovation is more common may significantly affect DSCs.

2.2.1 Market orientation and technology orientation. Strategic orientation research is a long-standing tradition in business research (Guo et al., 2020; Zhou et al., 2005), which pays attention to the details of a company’s general approach to formulating and implementing strategies in order to achieve long-term goals and maintain a competitive advantage in the market (Rezazadeh et al., 2016). It has been shown to be a key determinant of a company’s success and competitive advantage (Baía and Ferreira, 2019; Correia et al., 2021, 2022; Rezazadeh et al., 2016). Research on strategic orientation and DCs in the context of emerging technologies is rare or only addresses them implicitly. McLaughlin (2017) presented a conceptual overview of the DCs necessary for companies to succeed in emerging technologies, arguing that the speed of interaction and knowledge absorption has vastly increased in recent emerging technology cycles. Other qualitative research concerned with emerging information and communication technologies found that decision-makers tend to involve other actors and multiple individuals with differing views and perceptions in the decision-making process (Sunday and Vera, 2018).
<table>
<thead>
<tr>
<th>Type of relation</th>
<th>DCs considered</th>
<th>Effect on innovation performance</th>
<th>Source/Operationalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Side-by-side</td>
<td>Sensing, seizing, and reconfiguring as DCs</td>
<td>All DCs have a significant direct effect on innovation performance, besides multiple interaction effects with intellectual capital (as human, structural, relational and social capital)</td>
<td>Ali et al. (2021), Quantitative</td>
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<tr>
<td></td>
<td>Development, operations, management and transaction capabilities</td>
<td>Technical and economic performance with DCs as antecedents positively affects innovation performance</td>
<td>Alves et al. (2017), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Sensing, seizing, and transforming as DCs</td>
<td>Both DCs have a significant positive effect on radical innovation</td>
<td>Bogers et al. (2019), Qualitative</td>
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<td></td>
<td>Knowledge acquisition and knowledge-sharing capabilities</td>
<td>Effect on exploitative and explorative innovativeness</td>
<td>Cheng et al. (2016), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Technological opportunism defined as sensing and seizing capabilities</td>
<td>Effect on product, process, marketing, and other innovation</td>
<td>Cho et al. (2022), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Learning, integration and reconfiguration capabilities</td>
<td>Significant effect on product and process innovation</td>
<td>Edgar et al. (2022), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Learning, integrating, and reconfiguration capabilities as first-order constructs of DCs as second-order construct</td>
<td>DCs have a significant effect on innovation ambidexterity, moderated by innovation orientation</td>
<td>Farzaneh et al. (2021), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Sensing, seizing and transforming capabilities viewed individually, but orchestrated as DCs</td>
<td>Enables business model, process, and product innovation</td>
<td>Feiler and Teece (2014), Qualitative</td>
</tr>
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<td></td>
<td>Behavioural and strategic innovativeness as DCs</td>
<td>Impact on product, process, and market innovativeness</td>
<td>Ghosh and Srivastava (2022), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Five IT-enabled DCs (sensing, coordinating, learning, integrating, reconfiguring)</td>
<td>Positive effect of all DCs on product, process, and management innovation</td>
<td>Ilmudeen et al. (2021), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Coevolution of sensing, seizing, and transforming capabilities</td>
<td>All three dynamic capabilities positively affect innovation</td>
<td>Jantunen et al. (2012), Qualitative</td>
</tr>
<tr>
<td></td>
<td>Sensing, seizing, and reconfiguring are present at the same time</td>
<td>Impact on new business model performance</td>
<td>Jantunen et al. (2018), Quantitative/Qualitative (QCA)</td>
</tr>
<tr>
<td></td>
<td>Sensing, seizing, and transforming as DCs</td>
<td>Only seizing has a consistent positive effect on all measured dimensions of innovation performance, transforming is not significant, sensing weakly negative for some</td>
<td>Kump et al. (2018)</td>
</tr>
<tr>
<td></td>
<td>Interplay between sensing and seizing capabilities</td>
<td>Curvilinear relationship between sensing and seizing, and innovation performance</td>
<td>Naldi et al. (2014), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Sensing, seizing, and transformation abilities as DCs</td>
<td>All three DCs have a significant positive effect on service innovation</td>
<td>Plattfaut et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>DCs as second-order construct based on five first-order constructs (environment scanning, opportunity selection, employee engagement, commercialization of innovations, organizational learning)</td>
<td>DCs positively affect open innovation performance</td>
<td>Pundziene et al. (2022), Quantitative</td>
</tr>
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<td></td>
<td>DC as second-order construct based on six first-order constructs (innovation portfolio management, intrapreneurship, proactive adaptability, strategic renewal, value chain leverage, technology leadership)</td>
<td>DCs have a significant positive effect on innovative performance</td>
<td>Sicotte et al. (2014), Quantitative</td>
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<td></td>
<td>Dynamic innovation capability conceptualized as one factor</td>
<td>Dynamic innovation capability positively influences breakthrough innovation</td>
<td>Cheng and Chen (2013), Quantitative</td>
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<td></td>
<td>Marketing dynamic capability</td>
<td>Significant effect from marketing dynamic capabilities to radical innovation</td>
<td>Falasca et al. (2017), Quantitative</td>
</tr>
<tr>
<td></td>
<td>Dynamic capabilities</td>
<td>DCs have a significant positive effect on startup performance</td>
<td>Wu (2007), Quantitative</td>
</tr>
</tbody>
</table>

Table 1. Summary of the relationships between DCs and innovation performance (continued)
Strategic orientation can be conceptualized in several ways. The most frequently discussed distinction comprises market orientation and technology orientation (Guo et al., 2020; Randhawa et al., 2021; Zhou et al., 2005). Market orientation refers to a company’s focus on understanding customers, their needs and wants, and “entails pervasiveness and consistency of shared (customer-satisfaction-focused) values, which foster open functional communications, frequent customer contact, enquiries into customer problems, and shared efforts to solve those problems (…) MO includes three components: customer orientation, competitor orientation, and interfunctional coordination” (Peng and Lin, 2017, p. 313). Market orientation seeks to continuously gather and use information to reach a company’s strategic goals (Hamid Hawass, 2010). Companies with a strong market orientation are more likely to strive for a deep understanding of their customers and market knowledge (Ye et al., 2023), and are able to respond quickly to changes in customer preferences and needs (Monferrer et al., 2015). Consequently, some researchers argue that market orientation is synonymous with
customer orientation (Zhou et al., 2005). As such, they are capable of prioritizing the development of innovations that will have the greatest impact on their customers (Khan et al., 2020; Teece, 2007). In turn, a strong focus on market orientation can support the development of DCs by providing a clear direction for the company’s innovation efforts (Plattfaut et al., 2015; Sprafke et al., 2012). Other studies argued that market orientation may also result in learning myopia and hinder its ability to creatively respond to emerging technologies (Leng et al., 2015; Levinthal and March, 1993).

Technology orientation encompasses a firm’s dedication to harnessing and implementing technology in order to achieve its objectives (Peng and Lin, 2017; Rezazadeh et al., 2016; Zhou et al., 2005). Such companies are inclined to invest in emerging technologies and continuously refine their products and processes through technological innovation. This approach contrasts with the customer-driven focus of market orientation, as technology orientation adheres to the “technological push” philosophy (Zhou et al., 2005). This suggests that consumers are drawn to technologically superior products and services. As a result, technology-oriented organizations prioritize research and development, the acquisition of cutting-edge technologies, and the application of advanced solutions (Ahmad et al., 2018; Ali et al., 2021). Therefore, we propose the hypotheses:

**H2.** Market orientation has a direct positive effect on sensing capability

**H3.** Technology orientation has a positive effect on sensing capability

### 2.2.2 Organizational ambidexterity

Organizational ambidexterity is discussed in research as a combined measure of both explorative and exploitative innovation orientation (Cho et al., 2022; Gibson and Birkinshaw, 2004; He and Wong, 2004). Specifically, the relationship between ambidexterity and DCs has been a topic of interest in the literature, especially concerning its relationship to innovation performance (Peng and Lin, 2017; van Lieshout et al., 2021; Xin, 2018). Previous research suggests that ambidexterity and DCs are related but separate constructs (Wilden et al., 2016), proposing that ambidexterity plays an essential role in the development of dynamic sensing, seizing, and transforming/reconfiguring capabilities (Birkinshaw et al., 2016; Jurksiene and Pundziene, 2016; van Lieshout et al., 2021; Zimmermann and Birkinshaw, 2016). Some studies show DCs as a preceding factor for the development of ambidexterity (Farzaneh et al., 2022; Peng and Lin, 2017). Some researchers even argue that organizational ambidexterity is a DC itself (Carter, 2015; Garcia-Lillo et al., 2016; Kriz et al., 2014). However, some studies suggest that organizational ambidexterity is a mediating factor for obtaining competitive advantage (Birkinshaw et al., 2016; Jurksiene and Pundziene, 2016). Focusing solely on incremental or exploitative innovations can be risky, as companies may fall behind in the rapidly changing technological landscape. Conversely, concentrating exclusively on radical innovations may also be detrimental, as it may lead to neglecting the day-to-day business operations and customer needs (Gassmann et al., 2012; McLaughlin et al., 2008).

Striking a balance between these two innovation approaches is especially salient when organizational resources are limited and/or the environment is just too complex to pursue all (technological) innovation paths (Zabel et al., 2023), leading to trade-off decisions (Birkinshaw et al., 2016; Wilden et al., 2016). Therefore, a balanced approach to radical and incremental innovation may be worthwhile, leading to our hypothesis:

**H4.** Ambidexterity has a positive effect on sensing capability.

### 2.3 Effect of DCs on innovation performance

Finally, DCs play an essential role in enabling firms to achieve high innovation performance. DCs play a pivotal role in addressing emerging technological shifts and shaping the
competitive landscape in transformative markets. Researchers have highlighted the strong connection between DCs and the successful implementation and monetization of new technologies (McLaughlin, 2017), the execution of radical technological innovations (Chiu et al., 2016), and the realization of profits from these innovations (Teece, 2018b). DCs are crucial to supporting the development of new products, processes, and organizational structures that drive innovation and performance (Ali et al., 2021; Bogers et al., 2019; Farzaneh et al., 2021, 2022; Pundziene et al., 2022; Robertson et al., 2021; Siguaw et al., 2006).

While some studies diverged from the traditional differentiation of DCs and conceptualized them as one second-order construct based on sub-routines (Ilmudeen et al., 2021; Pundziene et al., 2022), other studies focused on these individual relationships between the single DCs (sensing, seizing, transforming) on innovation performance (Ali et al., 2021; Farzaneh et al., 2021, 2022; Gelhard and von Delft, 2016; Plattfaut et al., 2015). Plattfaut et al. (2015) conceptualized the three DCs as independent variables with a positive effect on innovation performance. In their research, they demonstrated that all three variables influence innovation performance. Accordingly, Kump et al. (2018) focused on a latent factor DC that is constituted by all three DCs and strongly influences innovation performance. Ali et al. (2021) conceptualized DCs as moderators of the relationship between intellectual capital and innovation performance. In their work, they demonstrate the direct effects of sensing, seizing, and transforming on innovation performance. Finally, Chiu et al. (2016) asserted a chain-like structure, where transforming/reconfiguring is related to radical innovation performance for an overview (see also Table 1).

Maijanen and Jantunen (2016) suggested that sensing, seizing, and transforming are linked in a one-directional manner, and transforming has a significant effect on innovation performance.

We thus formulate the following hypotheses:

H5a. Sensing capability has a positive effect on innovation performance
H5b. Seizing capability has a positive effect on innovation performance
H5c. Transforming capability has a positive effect on innovation performance

Furthermore, innovation performance can (and should) have a significant impact on a company’s overall performance (Božič and Dimovski, 2019). Companies that are able to effectively innovate, thus bringing new and improved ideas to the market, are more likely to stay competitive and be successful in the long-term (Teece, 2018b). They are more likely to be able to quickly respond to changes in the market, as they are used to innovating to address problems and challenges (Aramburu et al., 2013; Ferreira et al., 2019). Consequently, a company’s ability to innovate can positively impact its financial performance:

H6. Innovation performance has a positive effect on company performance

An overview of our research model with the included dependent and independent variables is provided in Figure 1.

3. Research methodology
3.1 Operationalization and questionnaire
We derived all operationalizations of the researched features based on items and scales, which are already established in the research, ensuring both accuracy and relevance. Concerning the DCs, we aimed at items that capture the meaning of the specific stage of DC. For instance, the sensing (SENS) construct, central to identifying market opportunities and environmental scanning, was adapted from seminal works by Kump et al. (2018), Plattfaut et al. (2015), and Mikalef and Pateli (2016). Similarly, our seizing (SEIZ) and transforming
(TRANS) constructs drew from studies emphasizing organizational adaptability in the face of market shifts for the former and organizational stamina and long-term planning for the latter (Kump et al., 2018; Plattfaut et al., 2015; Jantunen et al., 2018). Our metrics for market orientation (MARKO) and technology orientation (TECHO) were influenced by frameworks from Leng et al. (2015) and Zhou et al. (2005) respectively, highlighting the alignment with customer needs and the incorporation of cutting-edge technologies, as appropriate for vague but rapidly changing emerging market environments. Lastly, our measures for innovation performance (INNO_PERF) and company performance (COMP_PERF) took cues from Wang et al. (2018) and Yau et al. (2007) to adequately capture the effectiveness of new product developments and competitive edge, while not necessarily relying on mere profit numbers, which are often more akin to a proxy for company size.

As for our control variables, they were selected either based on their potential to influence the dynamic relationship between DCs and the two performance measures in the specific context of the XR industry or based on their widespread application as standard control in the literature. Concerning the former, the ‘number of DBEs’ where a company is active (i.e. number of DBEs) offers a perspective on a firm’s adaptability and reach in the digital space, and by extension, its innovative potential. The ‘number of target markets’ provides context on the company’s versatility and resilience, as diversification across sectors like communication, medicine, and others can indicate strategic adaptability. The degree of ‘XR specialisation’ (i.e. the percentage of revenue that depends on XR) offers insights into expertise and specialization in the industry examined, testing for effects on innovation for such companies and suggesting deeper insights and potentially stronger capabilities in the XR domain.

Concerning more general controls applied in the literature, ‘number of employees’ serves as a proxy for organizational size and resource capability, both of which can impact innovation dynamics. Lastly, the ‘age’ of the company was included, as older firms may have entrenched practices while newer firms might demonstrate agility; with both scenarios influencing their ability to innovate.

Since the survey was conducted in Germany, the items were translated from English into German. After selecting survey items based on the literature, the items were translated, and subsequently checked by the authors. We also engaged the expertise of a professional proofreader to further assure correct translation that preserves the original meaning.

We deployed our questionnaire via an online survey based on Enterprise Feedback Suite (EFS) survey software. The survey included basic information about the company (e.g. age,
number of employees, location), its products and services (e.g. focus on VR/AR/MR), and operationalized constructs (see Appendix Table A1). The survey was conducted between June 1 and July 4, 2022. Statistical tests were conducted by means of bootstrapping with partial least squares (PLS) path modelling (Hair et al., 2019). We evaluated the quality of our estimates based on standard model fit measures (e.g. Sarstedt et al., 2017) and the SmartPLS documentation.

3.2 Sample
The sample selection relied on a database obtained from a prior study on the XR industry in Germany (source withheld for blind review). Based on intensive, multi-method secondary research of publicly available information, the dataset comprises the entire population of XR-producing firms in Germany. In total, 1,613 companies working in the XR sector in Germany were identified, of which 1,456 companies could be contacted by e-mail. Of these, 224 individuals opened the survey; 221 began responding. 131 participants completed the survey. This corresponds to a response rate of 8.9%. The survey had an average completion time of around 21 min. To assure high data quality, participants who completed the questionnaire in an unusually short time (<5 min) or who showed inconsistent reply behaviour were excluded. In the end, the final survey sample consisted of \( n = 130 \) participants.

The companies surveyed vary in size, employing between 1 and 11,000 people, with an average of 170 employees. They were founded over a span of 112 years, from 1910 to 2022, with an average age of 16 years. A majority of firms (58%) were founded within the last decade. Of the companies surveyed, 55% established or introduced their XR division after their initial creation, while the remaining firms offered XR services from the start. 56.2% focus completely or predominantly on the business-to-business (B2B) sector, while only 7.7% are more focused on the business-to-consumer (B2C) market. In 2021, these companies generated between \( €10,000 \) and \( €17,500,000 \) in XR-related revenue, with an average of \( €670,279 \). The companies are located throughout Germany, with 42.2% based in six large urban agglomerations, including Berlin, Hamburg, Cologne, Munich, Düsseldorf, and Stuttgart.

Thirty-seven percent of the companies surveyed reported having up to two employees entirely dedicated to XR. However, 20% of the companies had between six and ten XR employees, and an additional 20% had at least eleven employees in this area. On average, these companies sold their services to 4.6 different industries (e.g. manufacturing, media, ICT).

3.3 Analysis
We used SmartPLS 3.3.5 to perform a factor analysis and structural equation modelling (SEM). To establish the assumed latent factors analysed in this paper, we conducted an exploratory factor analysis (EFA) (Netemeyer et al., 2003). EFA, as proposed by Netemeyer et al. (2003), is a cornerstone in discerning underlying structures within datasets, especially when the relationships between observed and latent variables are not well understood. This method helped us identify, validate, and refine our measurement scales, thereby ensuring the items used in our study were truly representative of their intended constructs. Two items were removed due to low factor loadings: One item from the latent construct transforming (TRANS_1) and one from market orientation (MARKO_3).

After establishing the latent factors through EFA, we used SEM to concurrently explore the multifaceted relationships between both observed and latent variables. Here, a confirmatory factor analysis (CFA) was conducted first, to check the factor structure of our measures for reliability and validity. Only items that withstood the selection criteria were preserved, which were met for all items left (see Appendix).
Second, the core hypotheses of our study were addressed using PLS path modelling. This method is particularly suitable for untangling complex models with commendable analytical performance, even with more modest sample sizes (Hair et al., 2019). By resorting to bootstrapping with 5,000 samples, we fortified our capability to probe the relationships outlined in our structural model.

Finally, after executing our estimations, the model was scrutinized against benchmark model fit measures, including normed fit index (NFI) and standardized root mean squared residual (SRMR) (e.g. Sarstedt et al., 2017, for details, see Section 4). To further ensure the validity of our methodology, we constantly checked each analytical step against the guidelines provided in the SmartPLS documentation (Ringle et al., 2022).

4. Findings

The confirmatory factor analysis produced satisfactory results for all constructs (see Appendix Table A2 for CFA factor loadings). The first independent variable, sensing, comprised identifying opportunities, scanning environments, detailing markets, and prioritizing opportunities, with loadings from 0.752–0.867 (α = 0.818). Seizing, i.e. reacting to changes, proposing new solutions and businesses, and developing alternative concepts, had the highest Cronbach’s alpha of the DCs (α = 0.844), and loadings ranging from 0.790–0.867. Transforming consists of persistent long-term project implementation, adaptation to business priorities, and persistence in change projects. A fourth item was eliminated due to low factor loadings. The reduced construct has an α = 0.808 and loadings between 0.763 and 0.909. Technology orientation showed loadings between 0.830 and 0.909 (α = 0.890). The second construct where an item was eliminated due to low factor loadings is market orientation (α = 0.643, loadings 0.756–0.770).

The two dependent variables were each measured by three items. Innovation performance (INNO_PERF, α = 0.884, loadings: 0.748–0.775) was operationalized by the return on investment, acceptance, and growth rate due to innovation. Competitive performance (COMP_PERF, α = 0.917 and loadings from 0.908 to 0.948) was measured by sales volume, success, and achievement of financial goals in relationship to competitors.

Internal consistency, as measured by Cronbach’s α, was good for all factors but one, with values far above the threshold of 0.7 (Nunnally, 1978). For MARKO, the Cronbach’s α values were above 0.6, which is considered acceptable for early exploratory research, such as in the case of the emerging technology context of XR (Churchill and Peter, 1984; Nunnally, 1978; Robinson et al., 1991). The low values may be due to the relatively small sample size compared to the number of estimates and PLS’s tendency to underestimate Cronbach’s α (Chin, 1998; Henseler et al., 2009). To ensure factor reliability, close attention was paid to meeting the more relevant composite reliability threshold (CR > 0.7) and convergence validity (AVE > 0.5), both of which were met for all constructs (see Appendix Table A2).

By analysing the Fornell-Larcker criterion (Appendix Table A3) and employing the heterotrait-monotrait (HTMT) ratio of correlations, the construct validity of the factors under investigation was assured, demonstrating their ability to differentiate from one another (for the factor cross-loadings, see Appendix Table A4). The HTMT values, as presented in Appendix Table A5, all lie beneath the 0.9 threshold recommended by Henseler et al. (2015) and Voorhees et al. (2016). Moreover, the variance inflation factors (VIFs) of the inner constructs range from 1.000 to 2.620, indicating the absence of any multicollinearity problems, as they remain well below the conservative threshold of 3.

SmartPLS goodness of fit results show an SRMR value of 0.061, which is within the acceptable range (<0.08; Hu and Bentler, 1999). The NFI at 0.711 is lower than the ideal value of 0.9, but still acceptable, given that smartPLS can systematically underestimate the NFI in small sample sizes (Hooper et al., 2008). To assess the potential presence of common method
bias in this study, Harman’s single-factor test was employed. The results indicated that such bias was not a concern, as less than 50% of the variance was accounted for by the creation of a single common factor, with only 30.9% being explained in this way (Harman, 1967).

4.1 Hypotheses testing
Following the extensive literature, we focused on innovation performance and competitive company performance as the dependent variables. This seems adequate, as the XR industry is strongly oriented towards innovation in order to ensure competitive advantage. The focus, therefore, lies on bringing new products and services to market, opening up new fields of technology, and attracting new customers. The results of SEM modelling are represented in Figure 2.

In terms of the research model, the main effects account for 29.2% of the variance in company performance ($R^2 = 0.292$) and 22.1% of the variance in innovation performance ($R^2 = 0.221$), indicating a moderate degree of explanatory power according to Chin’s (1998) classification. Furthermore, with the exception of one control variable, all others exhibit no significant influence on the dependent variable. As for the relationship between the DCs and innovation performance, only transforming has a direct and significant impact on innovation performance ($p = 0.018, \gamma = 0.279$), which in turn has a significant effect on company performance ($p < 0.001, \gamma = 0.501$). Controls were run on all factors. Only six out of 40 control-factor relationships proved significant. Three of them concerned the effect of the number of target markets on ambidexterity ($p = 0.015, \gamma = 0.210$), innovation performance ($p = 0.026, \gamma = 0.139$), and company performance ($p < 0.001, \gamma = 0.211$). Two factors were influenced by the number of DBEs a company is active in: ambidexterity ($p = 0.024, \gamma = 0.208$) and technology orientation ($p < 0.001, \gamma = 0.275$). Lastly, there was a negative effect from the XR focus of a company on ambidexterity ($p = 0.043, \gamma = -0.181$).

It is striking that in the chain of DCs, sensing has a significant effect on seizing ($p < 0.001, \gamma = 0.747$), seizing on transforming ($p < 0.001, \gamma = 0.390$), and sensing on transforming ($p < 0.001, \gamma = 0.362$), implying that each link in the chain has a significant impact on the others, with 50.5% of the variance of transforming being explained.

In relation to the antecedent constructs, market orientation, technology orientation, and organizational ambidexterity exert a significant positive influence on sensing (MARKO: $p = 0.006, \gamma = 0.213$; TECHO: $p = 0.010, \gamma = 0.249$; AMBI: $p < 0.001, \gamma = 0.282$), and explain 33.1% of the variance in sensing ($R^2 = 0.331$).

![Figure 2. Structural research model](image-url)
To shed more light on the interaction of the two strategic orientations, market and technology orientation, we took a closer look at the descriptive statistics for the average scores of the items. TECHO (mean: 5.89, standard deviation (SD): 1.10) and MARKO (mean: 5.19, SD: 0.84) were generally high. Only a small minority of companies scored below 4.0 (on a 7-point Likert scale), namely 7.7% for TECHO, and 8.5% for MARKO. Both scores differed for specific subjects by only 1.1 points on average, while just 15% of the cases had more than 2.0 points’ difference. We also checked whether the absolute difference between both factors produced significant effects in the main model. However, this variable proved to be insignificant. Therefore, the majority of firms were not oriented towards either TECHO or MARKO. They varied more with regard to the overall level of both constructs. A summary of the results for the hypotheses can be found in Table 2.

4.2 Discussion

The result of our analysis paints a comprehensive picture of how dynamic sensing, seizing, and transforming capabilities contribute to innovation and, in turn, to competitive performance in the rapidly evolving XR industry.

To begin with, the analysis demonstrates the cascading relationship between the constructs of sensing, seizing, and transforming. Sensing, characterized by the identification and prioritization of opportunities, greatly influences both seizing and transforming, but its effect is strongest on seizing, underscoring the sequential nature of the three DCs. This underscores the foundational importance of correctly identifying and prioritizing opportunities in the XR industry, predetermining the firms’ adaptability and long-term strategic development.

<table>
<thead>
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<th>Hypothesis</th>
<th>Std. coefficient</th>
<th>Accepted/ rejected</th>
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</thead>
<tbody>
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<td>H1a: Sensing capability has a positive effect on seizing capability</td>
<td>0.747***</td>
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</tr>
<tr>
<td>SENS → SEIZ</td>
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<td></td>
</tr>
<tr>
<td>H1b: Sensing capability has a positive effect on transforming capability</td>
<td>0.362***</td>
<td>Accepted</td>
</tr>
<tr>
<td>SENS → TRANS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1c: Seizing capability has a positive effect on transforming capability</td>
<td>0.390***</td>
<td>Accepted</td>
</tr>
<tr>
<td>SEIZ → TRANS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H2: Market orientation has a positive effect on sensing capability</td>
<td>0.213**</td>
<td>Accepted</td>
</tr>
<tr>
<td>MARKO → SENS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H3: Technology orientation has a positive effect on sensing capability</td>
<td>0.249**</td>
<td>Accepted</td>
</tr>
<tr>
<td>TECHO → SENS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H4: Ambidexterity has a positive effect on sensing capability</td>
<td>0.282***</td>
<td>Accepted</td>
</tr>
<tr>
<td>AMBI → SENS</td>
<td></td>
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<td>H5a: Sensing capability has a positive effect on innovation performance</td>
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<tr>
<td>SENS → INNO_PERF</td>
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<td>H5b: Seizing capability has a positive effect on innovation performance</td>
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<tr>
<td>SEIZ → INNO_PERF</td>
<td></td>
<td></td>
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<tr>
<td>H5c: Transforming capability has a positive effect on innovation performance</td>
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<td>Accepted</td>
</tr>
<tr>
<td>TRANS → INNO_PERF</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H6: Innovation performance has a positive effect on company performance</td>
<td>0.501***</td>
<td>Accepted</td>
</tr>
<tr>
<td>INNO_PERF → COMP_PERF</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Results for the hypotheses

Note(s): *p < 0.05, **p < 0.01, ***p < 0.001
Source(s): Authors own creation
At the same time, we found no direct effect of sensing or seizing on competitive performance. This underscores again the sequential nature of the three DCs – ‘leap-frogging’ from earlier stages of change directly to company performance improvements could not be observed. At the same time, this illustrates that the three DCs may be linked as a multiplicative product, akin to Kremer’s O-Ring theory (Kremer, 1993), where the weakest link may determine the output of the entire DC chain.

Regarding antecedents, we found that market and technology orientation as well as ambidexterity influence DSCs. The balance between the effect sizes (and in their descriptive statistics) of technology and market orientation on sensing suggests that companies are affected equally by technological advancements and market insights. This could indicate that a holistic approach to sensing is essential to remain competitive – at least in the case studied, which concerns a highly dynamic industry based on emerging (media) technologies.

Ambidexterity, that is the balance in approaching incremental as well as radical innovation activities, was also found to have a significant and substantial effect on DSCs. This also underscores the broad, equilibrated approach that sensing activities require when approaching innovations in such environments.

Finally, we could demonstrate the importance of innovation performance – which was in turn shown to be strongly affected by the DC chain’s last link, dynamic transforming capabilities – for improving overall company performance. In the case study, almost 30% of the variance of XR firms’ company performance could be explained by innovation performance. Given the multifaceted nature of company performance, this underscores the high relevance of innovation in dynamic, emerging technology markets.

4.2.1 Implications for theory. The findings of our comprehensive study on the role of DCs in the German XR industry have several profound theoretical implications. Our research contributes to the understanding of the sequential nature of DCs in emerging technology environments, their antecedents, and their impact of innovation on company performance.

First, we underscore the central role of DSCs for firms operating in emerging technology markets. The role of uncertainty or environmental dynamism has already been studied quantitatively (Girod and Whittington, 2017; Wilhelm et al., 2015), but has sparsely addressed the case of technological turbulence (Nagy et al., 2019). On a qualitative basis, previous studies found that the capacity to identify new business opportunities and partners profoundly affects a firm’s performance in emerging technology environments (Linde et al., 2021; Zabel et al., 2023). In this vein, our study demonstrates that sensing capabilities have a foundational role for ‘downstream’ DCs, affecting both seizing and transforming capabilities. This finding extends Teece’s (2007) original model, and adds nuance to the literature on the role of sensing in DCs by highlighting the need for a more holistic approach to leveraging DCs in emerging technology markets. The linkage from sensing to transforming activities may hint at the effectiveness of strategic initiatives designed at the corporate level based on market and technology insights. Here, larger companies were found to be at an advantage (Arend, 2014; Parida et al., 2016; Tavallaee and Cennamo, 2021; Zabel et al., 2023), as they are able to muster more company resources.

Second – developing this line of thought – our study emphasizes the sequential nature of DCs in emerging market environments. We found that the effect sizes are strongest from one stage to another, underscoring the ‘step-by-step’ nature of DCs. This provides a contrast to other studies of environmental turbulence, which found that selective DCs, e.g. business model sensing or strategic learning (Gelhard and von Delft, 2016; see also Cordero Páez et al., 2022; Naldi et al., 2014), may be sufficient to attain strategic performance in uncertain environments. One might argue that the higher turbulence of emerging technologies – where technological systems and possibilities may evolve rapidly and customer requirements are unclear and fast-changing – may represent a higher form of uncertainty compared to markets which are ‘only’ characterized by new products, market entrants, or competitive movements.
In those circumstances, a step-by-step approach – which is exemplified by methodological paradigms in entrepreneurship, such as the lean startup concept (Ries, 2017) – may be worthwhile, limiting risk and developing positive technological path dependencies (Chesbrough and Tucci, 2020; Fukuzawa, 2015; Maijanen and Jantunen, 2016). Resource limitations (or inflexibilities) can hinder DCs even in companies with relatively small path dependencies. Thus, DCs may deviate from the market strategy or organizational vision if the required components are unattainable. This encourages a bricolage approach, where firms adopt a ‘could-do’ mentality (Bicen and Johnson, 2015, p. 290), prioritizing immediate actions over long-term strategic planning. In contrast, larger organizations possess not only the ability to formalize their activities in these areas, they are in a position to allocate considerable resources as well.

Third, our study demonstrates the role of outward-looking strategic orientations for firms operating in emerging technology environments. We found that technology orientation exerts a slightly stronger influence than market orientation on DSC – which may reflect the importance of understanding and navigating the underlying technological complexity of the environment (Rezazadeh et al., 2016). At the same time, technology and market orientation do not seem to represent an either-or choice for the large majority of firms, since most firms in our sample place a comparable focus on both orientations (as signified by the relatively small SD of 1.1 between market and technology orientation). These findings fit well with previous qualitative research (Khan et al., 2020; Wilden et al., 2019; Zabel et al., 2023), pointing to the importance of having a balanced approach towards technology and market developments. Therefore, and building on the step-by-step argument made above, a lopsided ‘technology only’ approach may not lead to effective sensing activities.

Fourth, we discovered that organizational ambidexterity has the highest impact on sensing capabilities. It can thus be considered “complementary to dynamic capabilities as an essential element for the construction of these dynamic capabilities” (van Lieshout et al., 2021, p. 53). This finding underscores the need to balance innovative activities even in emerging technology markets, where radical or ‘leap-frog’ innovations might be expected (Jansen et al., 2006). Despite the emphasis on breakthrough innovations, the relevance of market needs and marketable products as a source of knowledge discovery should therefore not be underestimated – in line with studies showing that market orientation reinforces technological capabilities in an organization (Kafetzopoulos et al., 2023). Here, the analysis of control variables yields some interesting observations: ambidexterity (as well as innovation and competitive performance) significantly increased for firms that were active in more customer markets, were therefore taking in a broader set of inputs, and had to respond to more diverse customer demands. Since the firms in our sample were overwhelmingly active in the B2B sector, customer feedback was presumably at the same time more complex and easier to observe (or co-create together), leading to more differentiated offerings. Ambidexterity also increased when firms were active in more DBEs. This highlights the multi-homing requirements, since each DBE may have different requirements, opportunities, or levels of maturity (Altman et al., 2022; Teece, 2017).

Finally, the study sheds light on the relationship between DCs and innovation and (in turn) competitive performance for firms operating in emerging technology markets, which complements existing literature on this topic. On the one hand, the strong linkage between innovation performance and company performance was confirmed in the case of emerging technology markets. This is not particularly surprising, since product and process innovations play a significant role in establishing a competitive advantage in a market that is rapidly evolving (Farzaneh et al., 2021; McLaughlin, 2017; Teece, 2018b). On the other hand, our study reveals a strong linkage between transforming activities and innovation performance, in line with previous research (Baía and Ferreira, 2019). However, the moderate
explanatory power also points to the fact that other factors influence innovation performance. Therefore, a more specific examination of industry-specific DCs could be a potential next step for future research.

Interestingly, the dynamic sensing and seizing capabilities did not show significant results on innovative performance, at least underscoring that a comparable direct effect of earlier DC stages could not be replicated. This is in line with previous studies (Gelhard and von Delft, 2016). At any rate, other studies do show a linkage between sensing and seizing on innovative performance (Ilmudeen et al., 2021; Naldi et al., 2014; Plattfaut et al., 2015). In the same vein, Cho et al. (2022) showed that technological opportunism (encompassing sensing and seizing activities) affects explorative and exploitative innovation in manufacturing firms. This might illustrate the impact of industry characteristics on the effectiveness of sensing and seizing activities for innovation activities. The industries studied by Naldi et al. (2014, television production companies), Cho et al. (2022)/Ilmudeen et al. (2021, manufacturing), and Plattfaut et al. (2015, IT service provision) can be considered much more ‘straightforward’, as they presumably have a relatively stronger focus on incremental innovations, whereas the technological advances in the chemical industry (as in the case of Gelhard and von Delft, 2016) or the high technological affordances in the XR industry (as in this study) can be considered more demanding, thus constituting a much more uncertain and volatile business environment. Here, the results of our study emphasize the necessity of actually reconfiguring and scaling new initiatives to avoid getting stuck at the ‘prototype stage’ (Teece, 2007).

4.2.2 Implications for practitioners. Our study provides valuable managerial implications. The sequential nature of the DCs underscores the relevance of a step-by-step approach when engaging in emerging technology markets. Therefore, employing comprehensive paradigms like the lean startup methodology appears to be worthwhile, since it is not sufficient to sense developments and restructure the company accordingly – the ability to turn insights into new products and business models is also key. Here, our study underscores the importance of the ‘downstream’ DCs (notably transforming) for innovation and, in turn, company performance. To avoid stagnation at the ‘prototype stage’ of seizing capabilities, managers should place particular emphasis on transforming and scaling new initiatives.

That being said, our study made the foundational role of sensing capabilities in emerging technology markets clear. Managers in the XR industry should be especially attuned to this. Given the rapid evolution and multifaceted nature of XR technologies, it is paramount for industry leaders to maintain a keen sense for emerging trends, user preferences, and technological advancements. However, it is not enough to simply stay abreast of these developments. The real challenge, and the area where XR companies can differentiate themselves, lies in how effectively they translate this sensing into tangible products and solutions that meet market needs.

Here, managers might want to assure a balanced approach between technology and market orientation. This is significant, since the high technological complexity and fast advances might lure companies into focusing on a technological leap-frog strategy. Our findings show that technological orientation is important for effective sensing capabilities, which serve as a foundational DC. But the XR industry is as much about users as it is about technology. By emphasizing human-centric design and gathering market feedback early and often, XR firms can ensure their products resonate with users.

At the same time, companies rely on gathering market information in almost equal measure. This underscores the necessity for a balanced approach to sensing activities, which of course may represent a significant drain on company resources. XR managers should, therefore, consider investing in robust market research departments or collaborating with third-party firms specializing in XR market analytics. Such strategies not only facilitate better product development, they also aid in effective go-to-market strategies.
Another important insight concerns the role of organizational ambidexterity. Whereas smaller companies pursuing radical innovation might focus on a single product/technology combination (Bicen and Johnson, 2015), the companies in our sample – which were mostly active in the B2B sector – profited from a balanced approach of pursuing radical and incremental innovations at the same time. This might be due to the emergent nature of the technology, which limits the rapid scaling of a particular product-technology combination since the market is still embryonic. Incremental innovations on the other hand help sustain current operations and provide a valuable tool for growing the customer base, which in itself may serve as a basis of insight discovery (Zabel et al., 2023).

In the XR industry, incremental innovations can take the form of minor software updates, new modules for existing platforms, or usability enhancements, while radical innovations may involve breakthroughs in haptic feedback, augmented reality visualization, or even neural interfaces.

In equal measure, a balanced approach is also recommended with regard to incremental and radical innovation orientation. Ambidexterity in this regard helps companies strengthen their sensing capabilities. For XR industry practitioners, it becomes crucial to maintain a diverse product portfolio. Engaging with different segments of the XR market – from healthcare and education to entertainment and business solutions – can offer varied perspectives and open doors to unexpected synergies. It increases for firms active in different target markets or participate in different digital ecosystems, since the innovation requirements may differ between them. For XR firms, participating in interdisciplinary forums, conferences, and collaborative projects can provide a rich tapestry of insights and catalyse more holistic product development.

5. Conclusion
This research aimed to explain the role of DCs for firms operating in emerging technology environments. Looking at the case of the German XR industry, the sequential nature of DCs, the foundational importance of sensing, and its antecedents (market and technology orientation, organizational ambidexterity) have been analysed, as well as the DCs’ impact on innovation and, in turn, on company performance. By doing so, we contribute to the growing body of literature on DCs in emerging technology markets.

Our findings reveal the significance of the sequential nature of DCs, emphasizing the importance of a systematic, step-by-step approach in their development and execution. Sensing capabilities, in particular, are critical for success in emerging technology markets like XR. In any event, firms must also focus on seizing and transforming activities to maximize their potential, as the mere acquisition of knowledge is, as our study shows, not sufficient for realizing innovation. This view is consistent with the traditional view of innovation as fundamentally different from scientific knowledge or even classic research and development. Additionally, we highlight the importance of balancing technology and market orientation, as well as fostering organizational ambidexterity to ensure firms are prepared to seize opportunities and address challenges in the XR industry.

From a practical standpoint, our study offers valuable guidance for managers operating in the XR industry, but also in other emerging technology environments. By understanding the sequential nature of DCs and the need for a balanced approach between market and technology inputs, as well as radical and incremental innovations, managers can strengthen DSCs, which play a crucial role for effectively seizing business opportunities and renewing the company’s resource base.

Limitations of our study include the focus on the German XR industry, which is characterized by a strong focus on B2B models and a large share of small and medium-sized enterprises (Zabel and Telkmann, 2022). Other markets – such as the USA or significant
regional clusters like Silicon Valley – with a stronger emphasis on B2C models that are also home to ecosystem hardware providers may enlarge the scope of our findings. Also, the specifics of the XR industry – which is based on different technologies that are rapidly evolving – may limit the generalizability of our findings to other industries. Future research should aim to replicate and extend our findings in different contexts to further enrich our understanding of dynamic capabilities in emerging technology markets.

Our limited sample size may not encapsulate the full depth and intricacies of the underlying effects. This naturally calls for broader studies in the future with a more extensive participant base, which could yield more comprehensive and holistic insights. Concerning the original EFA, the elimination of specific items from the TRANS and MARKO constructs suggests potential refinements in future iterations of the research model. Also, despite the robustness in factor validity and reliability for most constructs, MARKO’s slightly lower Cronbach’s alpha might hint at nuanced dimensions within the market orientation in the XR context. On a more foundational level, our study is based on Teece’s (2007) DC model. The DC framework has spurred critical debates, particularly regarding the theoretical underpinnings of DC and the main criticism as being too abstract. As referenced in the literature on microfoundations, scholarly debates focus on the clarity of its main constructs and the intricacies of its initial conditions (Khan et al., 2020; Sprafke et al., 2012; Zabel et al., 2023). The chosen operationalization reflects the uncertain, dynamic nature of the XR industry, where sensing, seizing, and transforming activities may vary widely. Selecting specific activities would have created the risk of DC activities being reflected too narrowly. Given the understanding of DC activities in improving in these sectors as well (Zabel et al., 2023), further research could take up the emphasis that DC research has put on the analysis of the microfoundations of DCs (Arndt et al., 2022). Thus, future studies could query more specific (areas of) activities, possibly generating insights on the relative importance of DC microfoundations for innovation or company performance.

Furthermore, while we focus on DCs in general, the concept’s application to specific contexts might be fruitful. For example, dynamic managerial capabilities (DMCs) could be an influential construct in deciphering the entrepreneurial landscape (George et al., 2022). By emphasizing the roles of managers, DMCs offer a complementary lens to the traditional DC perspective. Analysing the evolution and intellectual structures of DMC literature juxtaposed with the limitations of DCs could pave the way for newer research trajectories.

On a similar path, further dissecting the core pillars of DMCs illuminates the relationship between managerial decisions, strategic change, and performance. Concerning managerial cognition, social capital, and human capital, there is an expansive realm to explore regarding their cumulative and individual impacts on strategic shifts and overall organizational outcomes (Helfat and Martin, 2015).

In conclusion, our research contributes to the understanding of dynamic capabilities in the context of emerging technology markets, offering valuable theoretical insights and practical implications for navigating the challenges and opportunities presented by the XR industry. As the market continues to evolve and grow, further research in this area will be crucial for ensuring the long-term success of firms operating in this competitive landscape.

References


Ball (Director), M. (2021), “Framework for the Metaverse”, available at: https://www.matthewball.vc/all/forwardtothemetaverseprimer


(The Appendix follows overleaf)
Appendix

<table>
<thead>
<tr>
<th>Construct</th>
<th>Factor loading</th>
<th>Cronbach’s alpha</th>
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Table A1. Questionnaire and construct overview
Constructs Cronbach’s α Composite reliability Convergence validity (AVE)
Sensing 0.818 0.880 0.648
Seizing 0.844 0.895 0.681
Transforming 0.808 0.886 0.723
Market orientation 0.643 0.807 0.582
Technology orientation 0.890 0.924 0.753
Innovation performance 0.884 0.928 0.811
Competitive performance 0.917 0.948 0.858

Source(s): Authors own creation

Table A2. Cronbach’s α, composite reliability, and convergence validity
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**Source(s):** Authors own creation
About the authors
Christian Zabel has been Full Professor for Innovation and Corporate Management at TH Köln – University of Applied Sciences since 2016. His research focuses on production and distribution processes/structures in digital media (especially online video and virtual/augmented reality) and the digital transformation of (media) companies. In his previous post he headed the product management of t-online.de, Germany’s largest online publisher. From 2008 to 2012 he was executive assistant to Deutsche Telekom’s CEO Rene Obermann, overseeing strategic cooperation with the media industry. Christian Zabel studied journalism in Dortmund and Brussels and political science at Sciences-Po Paris (IEP). Christian Zabel is the corresponding author and can be contacted at: christian.zabel@th-koeln.de

Daniel O’Brien has been a research associate at the Schmalenbach Institute for Business Studies at TH Köln, focusing on media-specific topics, since January 2022. Additionally, he is also been a research associate at the Chair of Innovation Management and Media at the Bauhaus-Universität Weimar since

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Source(s): Authors own creation

Table A5. Heterotrait-Monotrait ratio

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Source(s): Authors own creation
April 2023, specializes in the digitalization of media, media usage, technology acceptance, and quantitative empirical social research methods. Beyond academia, Daniel has worked in media companies, held teaching positions in the media and film industry, and performed freelance work for public institutions and companies. He continues to freelance as an author and maintains a passionate pursuit of creativity in his free time.