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Dynamic Capabilities to Manage Generative Artificial Intelligence in Digital Transformation Efforts

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Dynamic Capabilities to Manage Generative Artificial Intelligence in Digital Transformation Efforts

Research Paper

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Abstract. Incumbent firms face significant challenges due to rapid technological advancements, notably through generative artificial intelligence (genAI). By interviewing experienced digital leaders in a multiple-case study involving five organizations, this study elucidates eleven microfoundations, also referred to as low-level dynamic capabilities (DC). The specific focus centers on sensing, seizing, and transforming within the context of digital transformation (DT) efforts, offering insights into how organizations can navigate and leverage genAI to enhance their DT strategies. The identified microfoundations encompass 1) empowerment and knowledge utilization, 2) innovation ecosystem engagement, 3) organizational learning and openness, 4) interdisciplinary collaboration, 5) learning-driven innovation network, 6) organizational agility, 7) strategic leadership, 8) alignment and governance enhancement, 9) adaptive and informed culture, 10) organisational resilience, and 11) synergy creation. These foundations collectively provide a framework for leveraging genAI effectively from an organizational perspective.

Keywords: *Dynamic Capabilities, Generative AI, Artificial Intelligence, Digital Transformation, Multiple Case Study*

1 Introduction

Generative artificial intelligence (genAI) marks a transformative era for organizations and industries, unlocking new paths for enhancing competitive advantage (Alavi et al., 2024). Yet, the primary challenge emerges as firms must evolve their capabilities to navigate this swiftly changing technological domain successfully (Van Veldhoven & Vanthienen, 2022); 40% of the respondents of a large study (Ransbotham et al., 2019) report that they are grappling to effectively implement artificial intelligence (AI) technologies, reflecting a gap in leveraging technologies' full potential to reshape business models, processes and products (Hess et al., 2016, Fitzgerald et al., 2014).
Existing literature suggests that while genAI offers substantial opportunities for enhancing competitive advantage (Sætra, 2023), the payoff from such technological investments often remains unclear (Fitzgerald et al., 2014), underscoring the

significance of dynamic capabilities (DC) as a means to elucidate the leveraging of technological resources for strategic advantage. Furthermore, the development of DC is highlighted as crucial for advancing successful digital transformation (DT) (Vial, 2019). However, a key issue identified in the literature is the gap between the rapid advancement of genAI in industry practices and the pace of academic research (Stanford University, 2024), presenting a challenge in fully understanding and defining the capabilities required to harness genAI effectively. This paper responds to calls for more focused research on the organizational DC and conditions necessary for leveraging genAI by Banh & Strobel (2023) and Feuerriegel et al. (2024), emphasizing the need to closely examine and illuminate these capabilities to steer the technological possibilities of genAI in the direction for successful DT.

This qualitative multiple-case study enables the development of a nuanced understanding of how organizations utilize low-level DC, also referred to as microfoundations (Teece, 2023), to harness the transformative potential of genAI. The research question investigates: Which microfoundations, according to established organizations within the DC types of sensing, seizing, and transforming, are crucial for leveraging genAI in DT efforts? The study analyses five organizations, four from the private sector and one from public administration, drawing insights from thirteen experienced leaders through interviews and additional document reviews to provide a comprehensive perspective.

The research enriches the ongoing dialogue on DC within the information systems (IS) field (e.g., Steininger et al., 2022) by identifying eleven organizational microfoundations significantly impacting sensing, seizing, and transforming DT efforts. In doing so, the present study provides organizations with a guide on which aspects to concentrate on to leverage genAI.

2 Theoretical Foundation

2.1 DC to Achieve Competitive Advantage

DC theory evolved from Schumpeter's (1949) early insights on the displacing of incumbent firms by entrants, Porter’s (1980) five forces model to understanding the positioning of the firm, and through the resource-based view (RBV) emphasizing valuable, rare, imperfectly imitable and non-substitutable (VRIN) resources as sources of competitive advantage (Barney, 1991). Recognizing the static nature of RBV and the context-dependent attributes (Teece, 2023), the theory was extended to dynamic markets for which Teece et al. (1997) introduced DC as the means by which firms integrate, build and reconfigure competencies to address volatile environments. This concept was refined by Eisenhardt & Martin (2000), who argued that DC are specific, identifiable routines and that the competitive advantage comes from valuable, scarce, equifinal, interchangeable, and adaptable DC. Teece (2007) clustered the DC into sensing, seizing, and transforming activities, marking a shift toward understanding how firms dynamically reconfigure resources in response to environmental shifts. Based on this classification, numerous contemporary publications have been published (Warner & Wäger, 2019, Cannas, 2021).

Ordinary capabilities are the foundation for efficiency via key routines, also called best practices (Teece, 2014). Dynamically built upon these are microfoundations, which are understood as processes to adjust, combine, and innovate upon a) existing capabilities and b) development of new ones, which both are guided by the higher-order capabilities (Teece, 2018). The latter, categorized into sensing, seizing, and transforming, drive strategic adaptation and value creation (Teece, 2007, Teece, 2018). There are also other categorizations, such as that of Wang & Ahmed (2007); however, since the categorization according to Teece (2007) is predominant in the DT literature, the approach of other authors, e.g., Warner & Wäger (2019), is adopted. A balanced exploration-exploitation dichotomy is desired regarding the higher-order capabilities to address DT (Jöhnk et al., 2022, Teece, 2023). Further, it can be noted that higher levels prioritize entrepreneurial management over organizational routines, emphasizing innovation and strategic agility (Teece, 2023).

DC are equivalent to the higher-order capabilities within the dynamic level and are defined as the strategic and organizational routines and processes that allow firms to adapt, integrate, build, upgrade, and reconfigure resources and competencies to address rapidly changing environments (Teece et al., 1997, Eisenhardt & Martin, 2000, Wang & Ahmed, 2007). They are characterized by a forward-looking orientation and multidimensional nature, supporting particular activities, and typically require sustained commitments to specialized resources (Teece, 2023, Winter, 2003, Helfat & Winter, 2011).

2.2 Leveraging on DC to Succeed in DT

DT is the further evolvment from digitization and digitalization, employing a shift in how digital technologies need to be viewed to innovate business models and enhance value creation (Van Veldhoven & Vanthienen, 2022, Verhoef et al., 2021, McLaughlin, 2017). DT, triggered by the disruption of digital technologies, necessitates a unified vision, aligning the technologies with firm objectives to improve performance and necessitating leadership that fosters a sense of urgency for transformation (McLaughlin, 2017, Singh & Hess, 2017, Vial, 2019, Fitzgerald et al., 2014).

DT relies on DC for successful implementation, highlighting the importance of systematically adapting to changes in today’s market (Winter, 2003, Vial, 2019). DCs in DT are relatively unexplored (Ellström et al., 2022), although they serve as a critical lens for understanding the DT process, especially in incumbent firms (Warner & Wäger, 2019). DC are intricately linked to digital maturity, with Marx et al. (2021) and Vial (2019) indicating that a firm's DC enhance its digital maturity.

DC, comprising discovering and creating opportunities, sensing and seizing capabilities, and executing ones, transforming capabilities, are essential for firms to effectively navigate the intricacies of DT (Teece, 2007, Warner & Wäger, 2019).

Sensing entails the vigilant identification, development, and interpretation of new opportunities and threats through a blend of scanning, learning, and creating (Teece, 2007), underpinned by sub-DC like scouting, scenario planning, and mindset crafting

(Warner & Wäger, 2019), to adapt to technological and environmental changes (Day & Schoemaker, 2016).

Seizing involves the strategic agility to capture value (Ellström et al., 2022) from identified opportunities, necessitating changes across the organization to effectively utilize potential business prospects through rapid prototyping and balancing digital portfolios (Yeow et al., 2018, Day & Schoemaker, 2016).

Transforming entails the continuous renewal and reconfiguration of organizational routines (Yeow et al., 2018) and structures essential for sustained growth as firms evolve and adapt to environmental changes (Teece, 2018). This capability is underpinned by "redesigning internal structures", and "improving digital maturity" to ensure the firm remains competitive and agile in the digital age (Warner & Wäger, 2019).

2.3 genAI Requiring Adapted DCs for DT

Digital technologies act as a pivotal driver in DT, enhancing firms' abilities to innovate, exploit external knowledge, and engage in novel business models, thereby fundamentally transforming business strategies, operations, and stakeholder relationships for competitive advantage (Bharadwaj et al., 2013, Kraus et al., 2021).

genAI is underpinned by deep generative models (DGM) as emergence from deep learning models, which are a subset of machine learning (Banh & Strobel, 2023). genAI is revolutionizing industries by enhancing knowledge management, products, services, and customer support through its ability to compress the information layer and generate knowledge from vast datasets (Mondal et al., 2023, Alavi et al., 2024). This technology, capable of producing diverse and realistic content across various input and output types (Banh & Strobel, 2023), is positioned as a disruptive force in the digital realm (Dwivedi et al., 2023), pushing the boundaries of innovation and redefining the management of AI in the new era of IT management, despite the ethical challenges it presents (Berente, 2021, Stanford University, 2024).

Distinct from exploring the technical capabilities of the technology itself, such as those highlighted by Feuerriegel et al. (2024) regarding generative pre-trained transformers (GPT) and their application in conversational agents, and examining the augmentation of human capabilities for enhanced speed and efficiency (Dwivedi et al., 2023), the focus should center on DC of a firm. Leveraging incremental and radical innovation (Mariani & Dwivedi, 2024) through genAI for DT activities is crucial. With this, the approach outlined by McLaughlin (2017) is adopted, concentrating on how organizations can develop sustainable DC to leverage a particular technology effectively to achieve competitive advantage. This emphasis lies in aligning with ever-evolving market conditions and operational challenges to ensure that the integration of genAI contributes substantial business value. As a consequence, DC and a deepened understanding of their underlying microfoundations are needed to excel in leveraging genAI.

3 Research Methodology

3.1 Study Design

Given the complex nature of DC and their critical role in navigating the technological shifts brought about by genAI, this study adopts an empirical case study method, aligning with the approach recommended by Helfat & Winter (2011) and successfully employed in related research by Ellström et al. (2022) and Jöhnk et al. (2022). This methodological choice is underscored by its effectiveness in deeply exploring contemporary phenomena within their real-world context (Yin, 2018). This research is characterized by a multiple case study design, incorporating three units of analysis (Yin, 2018): sensing, seizing, and transforming activities. Numerous case studies serve as a pivotal research strategy for developing theory, where cases are selected to illuminate and extend relationships among constructs, thereby creating a more robust study grounded in diverse empirical evidence (Eisenhardt & Graebner, 2007).

The four case study tactics were meticulously applied to ensure the quality of the research design. These four principles encompass external validity, construct validity, reliability, and internal validity (Yin, 2018). External validity involves replication logic, which is addressed through the diverse selection of cases examined (see Chapter 3.2). Construct validity, addressed not only during data collection but also during data aggregation, includes triangulation with primary and secondary data in this study (see Chapter 3.3). Reliability is ensured through the case study database (see Chapter 3.3). Finally, internal validity, addressed during data analysis, is maintained through systematic coding during the aggregation of insights (see Chapter 3.4).

3.2 Case Selection and Description

In the case selection process, adherence to theoretical sampling, as outlined by Eisenhardt (1989), resulted in the identification of five cases at various stages of the AI-driven DT process (see Table 1), as described by Taherizadeh & Beaudry (2023).

Table 1. High-level Comparison of the Cases

Case **Dimension**	A	B	C	D	E
Leading the Transformation	◑	◕	◑	◑	◔
1. Evaluating Transformation Context	●	●	●	●	◕
2. Auditing Organisational Readiness	◑	◕	◕	◑	◔
3. Piloting the AI Integration	◑	◕	◔	◔	◔
4. Scaling the Implementation	◔	◑	◔	◔	◔

This diverse selection, indicative of the representativeness principle suggested by Dubé & Paré (2003), encompasses the following organizations:

Case A, an insurance company, is integrating genAI use cases into its existing governance through a company-wide AI initiative, initially focusing on setting up an internal knowledge platform based on genAI to expedite information access for employees. Their (gen)AI approach is based on a maturity model of Gartner, contrasting complexity and use versus skills and maturity degree.

Case B, a retail and consumer goods firm that has merged its marketing and IT units, is proficient in data analytics and has defined seven pillars of digitalization, identifying meaningful genAI use cases for each. They have deployed genAI chatbots for customer interaction and leverage the technology for internal marketing enhancements.

Case C, operating in automotive, is enhancing its data-drivenness and digital maturity through a transformation tube map with AI as a core pillar. Currently, they are training employees to use integrated genAI solutions with *Promptathons*.

Case D, a global mobility group excelling in robotic process automation and conducting various genAI proof of concepts, sees significant advantages in managing organizational norms that vary significantly by country through the standardization capabilities of genAI.

Lastly, Case E, a large governmental entity, aims to boost attractiveness and gain insights through a sandbox approach to exploring regulatory and innovative (gen)AI questions, complemented by a DT unit evaluating (gen)AI options for public benefit.

3.3 Data Collection

Interviews were selected for their efficiency in collecting rich data (Eisenhardt & Graebner, 2007), involving a diverse group of pioneers, investigators, and experimenters (Ransbotham et al., 2019). In total, twelve semi-structured interviews were conducted:

Table 2. Overview of Interview Participants

Case	Industry	Employees	ID	Interviewee(s)
A	Insurance	> 3’000	A1	Head of Advanced Analytics Solutions
			A2	Lead BI Solutions & Architecture
			A3	Head of BI & Analytics
B	Retail and Consumer Goods	> 95’000	B1	Head of Digital and Customer
			B2	Head of AI / ML Analytics
C	Automotive	> 7’000	C1	Head of Data and Advanced Analytics
			C2	Head of Customer Centricity; Customer Retention Specialist
D	Mobility	> 70’000	D1	Chief Digital Officer
			D2	Head Digital Solutions & Data Management
			D3	Digital Solutions Manager
E	Public Administration	> 30’000	E1	Lead Digital Transformation
			E2	Project Lead New Technologies

The interview questions targeted the sensing, seizing, and transforming efforts regarding genAI in DT.

Multiple sources of evidence were used for triangulation (Dubé & Paré, 2003). In addition to the interviews, supplementary secondary data consisting of 13 documents, both internal and publicly available, was considered to ensure the quality of the research findings. These secondary sources included annual reports, internal strategy presentations, project presentations, and company websites, which complemented the interview material. This approach helped close potential knowledge gaps and ensured a coherent representation of the cases studied. All documents were stored in a central case study database.

3.4 Data Analysis

Interviews were digitally recorded and transcribed, except for one where notes served as the basis for analysis. The transcripts and secondary data underwent systematic coding (Dubé & Paré, 2003) using qualitative data analysis software, adhering to the guidelines set by Yin (2018) and employing an exploratory coding method of in vivo coding as per Strauss & Corbin (1990). Initially, 308 open codes were generated and subsequently clustered in each unit of analysis (sensing, seizing, transforming). Similarities and differences were consolidated to streamline data reduction (Dubé & Paré, 2003), facilitating within-case analysis and cross-case analysis aiming for theoretical replication (Eisenhardt, 1989). This approach enabled the meaningful extraction of microfoundations, respectively, low-level DCs discussed in the cases to address the overall research question. The methodology of Gioia et al. (2012) was applied for data analysis, deriving a total of 118 first-order concepts. These concepts were then organized into 37 second-order themes and ultimately into 11 aggregate dimensions, enhancing the depth and comparability of the findings. For clarity, Chapter 4 visually represents the derivation of second-order themes to aggregated dimensions for each unit of analysis.

4 Results

4.1 Microfoundations of DC Category Sensing

Empowerment and Knowledge Utilisation: Organisations like cases A and D utilize insights workshops to contextualize genAI use cases, enhancing their operational framework, as mentioned by interviewee D1: *"We know what is technically possible, but not necessarily what the business needs. Therefore, we must ensure the technology's tangibility in discovery workshops"*. Case B emphasizes leadership training for crowdsourcing genAI use cases alongside playgrounds that foster creative experimentation. Similarly, Case D's efforts to translate technology into actionable solutions, facilitated by internal advocates, highlight the critical role of equipping employees with the necessary knowledge and resources for effective genAI innovation and application.

Innovation Ecosystem Engagement: Engagement with the ecosystem is vital, as evidenced by case C's platforms for cross-disciplinary exchange and case E's sharing of expertise at the European Council. Moreover, case D highlights the critical need to define genAI's potential value from the start, using the ecosystem as a lever to validate user-centricity. Across all examined cases, strategic partnerships with major industry players and consultancy relationships facilitate a knowledge pull that empowers employees and enriches internal expertise. In addition, case B's market benchmarkings and case C's trend radar offer orientation towards market developments.

Organisational Learning and Openness: Cultivating a digital openness culture is crucial for adapting to genAI, promoting an environment that values curiosity, critical reflection, and outside-the-box thinking, observed in case B. Case D measures and promotes a digital mindset through annual assessments and targeted training, emphasizing the importance of scrutinizing as a core competency. Further, case E focuses on creativity enhancement within its innovation hub, recognizing the challenge of balancing resource constraints with the need for inspiring encounters that fuel iterative learning and innovation.

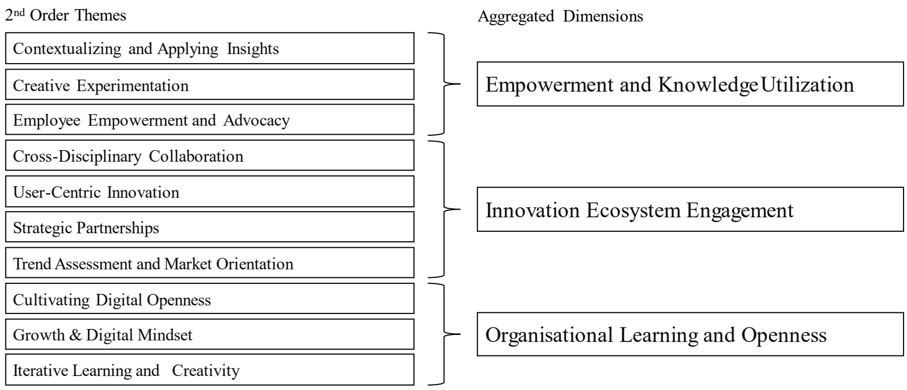

Figure 1. Data Structure on Sensing Microfoundations to Leveraging genAI

4.2 Microfoundations of DC Category Seizing

Interdisciplinary Collaboration: Cases B and C showcase the critical role of sharing successes in multidisciplinary collaboration to make technology implications visible, enhancing decision-making and strategic flexibility. This approach emphasizes collecting internal learnings before external genAI application to strengthen decision capability, with case E directly applying learnings in services due to its unique mandate.

Learning-Driven Innovation Network: Starting small for complexity reduction and experimental mindset in case B highlights the importance of empirical testing and real-world validation of genAI use cases. For case E, formalizing knowledge into guidelines fosters its usability, facilitating knowledge sharing and transfer. All organizations engage in experimenting with PoC for hypothesis testing, underlining the necessity of ongoing upskilling as integral, in alignment with Jackson et al. (2024)'s insights on workforce training for effective genAI utilization.

Organizational Agility: Cases A and B focus on fostering adaptability through contextual understanding and sharing success stories, highlighting the need for continuous organization-specific adaptation and strategic alignment. Case D's resource optimization and exploring scaling effects in case B demonstrate a commitment to leveraging insights for multidimensional applications, ensuring governance flexibility.

Strategic Leadership: Case E's emphasis on operationalizing innovations for value creation and case A's balance of value, investment, and risk highlight the importance of leadership engagement in assessing the justification of risks and expenditures. This is strengthened by Fitzgerald et al. (2014), who state that leading instead of doing technology-based transformations depends on leadership frameworks. Across all examined cases, strategic initiative planning involves prioritizing. As interviewee B1 explains: *"We prioritize our resources based on where we create the greatest customer value"* for maximum value addition and impact enhancement. This resonates with the broader strategic efforts to bundle decentralized initiatives, as mentioned in case E, and address psychological stakeholder reactions noted by Kanitz et al. (2023).

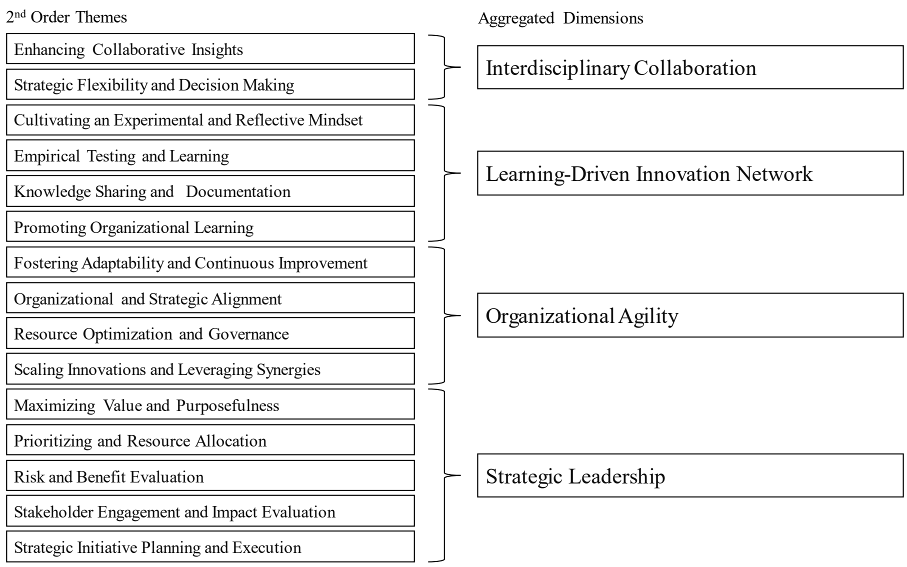

Figure 2. Data Structure on Seizing Microfoundations to Leveraging genAI

4.3 Microfoundations of DC Category Transforming

Alignment and Governance Enhancement: Change leads serve as multipliers for transformation, as observed in case E. Further, cultivating organizational synergy through shared experiences in case A and case E can be seen as an accelerator. This strategic alignment extends to formalizing scalability through structured methodologies in case A and harmonizing processes in case B, facilitating a coordinated approach to genAI adoption by connecting the dots of the insights gained.

Adaptive and Informed Culture: Continuous learning and knowledge sharing seem crucial for navigating the genAI landscape. Case B's emphasis on upskilling for comprehension, alongside case C's efforts to centralize knowledge, underscores the importance of an enabled workforce. Case A's approach to making insights actionable reflects a commitment to internal knowledge development that is relevant to fostering an innovative environment where genAI can thrive. Interviewee A1 points out: *"We provide them [the employees] with [genAI] dashboards they can operate themselves, allowing them to derive benefits via self-service."*

Organizational Resilience: Organizational resilience is strengthened by integrating critical reflection abilities, as demonstrated by cases A and B, and incorporating adaptive mechanisms like humans in the loop in case D. For scalable genAI solutions, visionary thinking, as encouraged by case C and case D, is closely linked to maintaining agility as a critical resilience factor as has been experienced in case E. Flexibility is enhanced by manifesting vision into tangible experiences for impactful reflections and adaptable actions in response to challenges, as practiced by case D.

Synergy Creation: Identifying and leveraging interdependencies, as case A shows, is critical to creating synergies and enhancing genAI utilization. Case B's establishment of a competence center for strategic coordination exemplifies how organizations can facilitate scaling, ensuring that genAI's transformative potential is fully realized and integrated into organizational strategies for maximum impact.

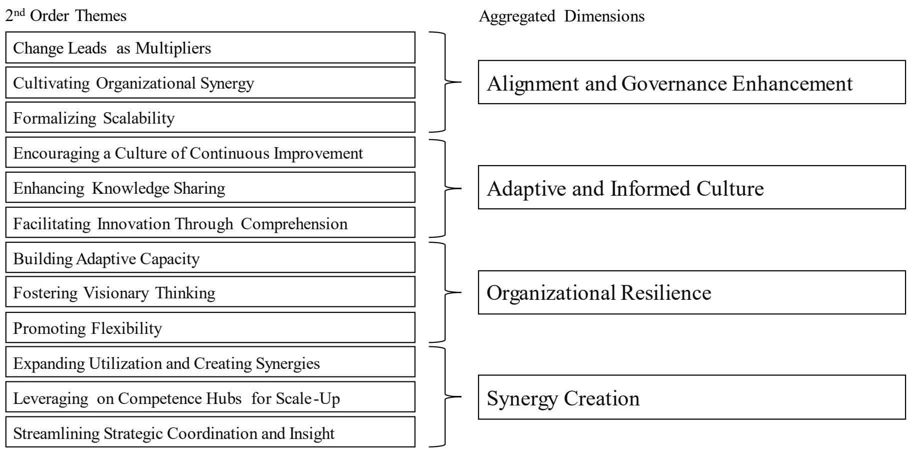

Figure 3. Data Structure on Transforming Microfoundations to Leveraging genAI

4.4 Putting it Together: Microfoundations of DCs for Leveraging genAI in DT

Organizations aiming to uncover genAI opportunities in DT efforts should focus on microfoundations of sensing, which center on empowering their workforce, leveraging knowledge, engaging with the ecosystem, and fostering learning and openness. Maximizing the value of genAI during seizing requires microfoundations evolving around interdisciplinary collaboration, cultivating a learning-driven innovation network, enhancing organizational agility, and demonstrating strategic leadership as microfoundations. Lastly, when it comes to transforming and thus scaling by constantly restructuring, enhancement of alignment and governance, fostering a culture that is adaptive and well-informed, promoting organizational resilience, as well as generating synergies are needed as microfoundations.

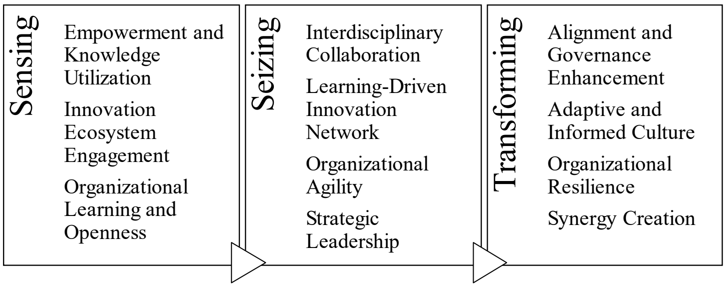

Figure 4. Microfoundations of DC to Leveraging genAI for DT activities

Drawing on the findings, this study elucidates how the delineated microfoundations can assist organizations in leveraging genAI within their DT endeavors. Advancing data foundations, enhancing quality and transparency, and fostering compliance and ethics awareness are pivotal information technology capabilities, as highlighted by Banh & Strobel (2023). However, the effective leverage of genAI transcends mere technological advances, necessitating a symbiotic integration of technology and human interaction (Agrawal, 2023), which is the latter this research aims to address. Swiftly responding to and managing new technologies (Fitzgerald et al., 2014) does not necessarily mandate a first-mover stance, a strategy exemplified by case B. In adopting a more measured approach, organizations can systematically apply these valuable microfoundations, building upon them progressively. Consistent with Eisenhardt & Martin (2000), repeated practice is underscored as a critical learning mechanism within the DC framework, facilitating the integration of genAI into DT strategies.

5 Discussion of Results

5.1 Theoretical Contribution and Practical Implications

This multiple-case study expands the discourse on DC as extensively explored within IS research over recent decades (Steininger et al., 2022). It specifically explores the interplay between genAI and the essential microfoundations of DC in DT. By integrating insights from genAI studies and research on DT, including works by Ellström (2022) and Warner & Wäger (2019), this investigation bridges critical areas of inquiry, providing a comprehensive view on leveraging genAI in DT efforts.

This contribution aims to provide practitioners adopting genAI and seeking to establish functional DC at an organizational level with actionable and meaningful microfoundations. It seeks to empower them to effectively maximize the technological component to accelerate DT (Warner & Wäger, 2019). As observed across all cases dealing with genAI adoption, it is advisable to start small and then scale up to prevent overwhelming individuals and address complexity, in line with suggestions by Dwivedi et al. (2023). The conceptualized non-technical microfoundations are intended to aid in the value generation of genAI in DT efforts.

5.2 Limitations and Directions for Future Research

This study, while providing valuable insights through qualitative exploratory research and leveraging the knowledge of experienced executives, acknowledges certain limitations. The multiple case study represents a snapshot in time without quantitative substantiation, relying exclusively on qualitative data. Additionally, although a diverse range of organizations in terms of sectors, sizes, and maturities (see Table 1) were selected to obtain a comprehensive view, the limited number of interviews suggests that expanding the sample and testing the findings with more case partners could enrich the research. Moreover, biases in the coding process cannot be completely eliminated, as the coding was performed by a single individual. Finally, while attempting to cover a broad spectrum of organizational contexts, it remains uncertain how the microfoundations of DC might evolve with more advanced stages of genAI adoption, a comparison that this study's scope cannot fully address.

In this research, we have concentrated on non-technical DC as defined by Dwivedi et al. (2023). Exploring technological DC presents an exciting field for future research. While there has been significant attention to genAI as an entity within socio-technical systems across various applications such as text, image, video, speech, and code generation (Banh & Strobel, 2023, Dwivedi et al., 2023, Feuerriegel et al., 2024, Mariani & Dwivedi, 2024), there remains a gap in understanding how genAI itself can create capabilities in regards of sensing, seizing, and transforming. This gap, noted as well by Dwivedi et al. (2023), represents an intriguing field for research, opening up discussions on the autonomous development of organizational capabilities through genAI.

6 Conclusion

In conclusion, technology represents merely one component of the broader picture (Vial, 2019). This research identifies eleven pivotal microfoundations distributed across the DC framework, three for sensing, four for seizing, and four for transforming. This conceptual work enriches the ongoing discourse on genAI and its intersection with DC in the DT landscape.

The eleven concluding microfoundations are designed to be incrementally applied across the three categories of DC. It is crucial to recognize that the sub-DC of seizing builds upon the sub-DC of sense, and similarly, the sub-DC of transforming builds on the sub-DC of sensing and seizing (Warner & Wäger, 2019), highlighting the interdependent and layered nature of scaling genAI.

Furthermore, DC's microfoundations contribute to the optimal allocation of organizational focus, enabling genAI’s beneficial and scalable use. They offer organizations a source of inspiration on where to direct their efforts meaningfully to enhance the sustainable impact of genAI.

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