THESIS FOR THE DEGREE OF LICENTIATE

Framing Generative Technology for Dynamic Capabilities:

A case study of AI platform implementation in large enterprises

MARIA KANDAUROVA

Department of Technology Management and Economics

CHALMERS UNIVERSITY OF TECHNOLOGY

Gothenburg, Sweden 2022

Framing Generative Technology for Dynamic Capabilities:
A case study of AI platform implementation in large enterprises
MARIA KANDAUROVA

Technical report no L2022:138

Division of Entrepreneurship and Strategy
Department of Technology Management and Economics
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 1000

Chalmers Reproservice
Gothenburg, Sweden 2022

Abstract

Organizations are increasingly turning to generative technologies known for their inherent dynamic, malleable, and context-agnostic nature to innovate and create a competitive edge. As generative technologies offer virtually unlimited potential applications, organizations are constantly challenged to identify appropriate applications. To date, our knowledge of how organizations implement these technologies to deliver the anticipated outcome is still limited.

Inspired by the recent calls on the nature and management of one such generative technology, Artificial Intelligence (AI), this thesis aims to provide insights on how large organizations make sense of the open-ended nature of AI, and how such framing impacts how they leverage its potential for dynamic capabilities and organizational innovation. As large organizations are typically characterized by established processes, routines, and accumulated collective experiences, this would suggest particularly challenging dynamics when implementing a highly versatile technology.

Following an abductive research approach and a qualitative multiple-case study methodology, this thesis puts forward two empirical papers covering the implementation of an award-winning conversational AI (CA) platform and its applications, i.e., chatbots and voicebots, across eight large organizations.

Findings indicate that the implementation trajectory differed strongly across those organizations. In all organizations, there were initially inter and intra-organizational incongruent interpretations towards a suitable application of the platform and its use. This illustrates the uncertainty that comes with the open-ended nature of generative technologies, which is in line with prior research. However, contrary to the predominant notions that such incongruencies hinder successful implementation, this thesis illustrates how some organizations actively sought these 'creative conflicts' to align diverse perspectives and subsequently uncover new opportunities for dynamic capabilities and organizational innovation. Notably, those organizations shifted from an outcome-oriented to an opportunity-oriented implementation strategy by crafting and employing various cognitive and behavioral processes allowing further exploration of the platform's generative potential.

Two main practical takeaways can be drawn from this thesis. First, this thesis illustrates that organizations still often evaluate generative technologies using traditional efficiency-orientated key performance indicators (KPIs) that prioritize short-term cost reduction. Such KPIs may be unsuitable for generative technologies that require organizational flexibility to explore the long-term strategic applications related to the 'horizon of opportunities' that the generative technology can offer. Second, organizations should be open to rethink their processes, tactics and routines in which they engage in order to realize the full benefits of emerging generative technologies. This is especially relevant for large organizations that have strongly established processes. Findings from this thesis suggest that seeking out and learning from 'creative conflicts' is key to adapting those processes, routines, and tactics. This thesis refutes a deterministic view on technology and its implementation. It suggests that organizations must engage in open processes of learning and reframing in order to effectively utilize increasingly malleable technologies.

Keywords: generativity, technology implementation, AI, framing, incongruences, dynamic capabilities, organizational innovation

List of appended papers

Paper I - Enhancing Generative Capacity through Tactical Framing: A Multiple - Case Study of an AI Platform

Kandaurova, M., and Bumann A.

This paper is an in-progress manuscript at the time of writing this thesis. The aim is to submit it to a relevant IS journal.

Contribution: Collected and analyzed data, conceptual development, and writing of the paper.

Paper II – How do organizations develop their dynamic capabilities and achieve organizational innovation using a generative AI platform?

Kandaurova, M., Ngwenyama, O., and Teigland, R.

This paper is an in-progress manuscript at the time of writing this thesis. The aim is to submit it to a relevant SIS journal.

Contribution: Collected and analyzed data, conceptual development, and writing of the paper

Acknowledgements

This thesis marks a halfway point in my PhD journey, and I wish I could say that it was "smooth sailing". In reality, there have been a few bumps. I think many of my PhD colleagues share the uncertainty and difficulty associated with the rocky terrain of doctoral research. The external circumstances such as the pandemic and the aggressive and shameful war of my home country against a dear-to-my-heart nation made it all more challenging for me to reach this point. Nevertheless, I kept on walking, as my best friend would often remind me that "the one who keeps walking, will cross the finish line." This journey would not have been possible without the support of many to whom I extend my gratitude.

Firstly, I want to thank my supervisor Robin Teigland and my co-supervisor Ojelanki Ngwenyama for their feedback, despite their busy schedules. Robin, I appreciate your inexhaustible energy in believing in my abilities and supporting the success of this thesis. Ojelanki, thank you for your guidance. When we meet, our interactions always remind me of why I embarked on this journey in the first place.

Secondly, I want to thank my spouse, Ivan Gogolev, for his encouragement and continuous support during my PhD. I would not have been able to reach this point without you. You are the one who encouraged me to accept this PhD opportunity, so I would not have regrets for not trying. You have been my inspiration, personally and professionally. Thank you very much for your guidance and the encouragement to enrich my potential. Thank you for believing in me in the moments of uncertainty, especially when I doubted my capabilities the most. Throughout my personal ordeal, you have always been my rock. For that, I am forever grateful to you!

Thirdly, I want to thank my dear officemates, Ida and Martin for sharing the PhD successes and struggles. Special thanks go to Adrian for his tremendous support, both personally and professionally. My PhD journey would have been very lonely without you and your ideas.

Finally, I want to thank my dear Gogolevs, Nina and Mikhail. You have been extremely kind and supportive to me throughout all these years. I am very lucky to have you!

Maria Kandaurova,

Göteborg, October 2022

Table of Contents

1. Introduction

To innovate and create a competitive edge, organizations are increasingly turning to pervasive digital technologies characterized by generativity, i.e., they are inherently dynamic, malleable, and context-agnostic (Yoo, Boland, Lyytinen, & Majchrzak, 2012; Zittrain, 2008). In this thesis, I investigate artificial intelligence (AI), as one example of generative technology that holds the promise to offer a wide range of value propositions and enable organizational innovation (Benbya, Davenport, & Pachidi, 2020; Benbya, Pachidi, & Jarvenpaa, 2021; Raisch & Krakowski, 2021; von Krogh, 2018).

Prior literature has stressed the importance of technology for enhancing organizations' dynamic capabilities, i.e., sensing, seizing, and transforming processes triggered by the opportunities and threats presented in the environment (Pavlou & Sawy, 2010; Roberts & Grover, 2012; Sandberg, 2014; Schilke, Hu, & Helfat, 2018). Traditionally, technology has been viewed as a functional resource that is 'expected to do what its designers intend it to do' (Orlikowski & Iacono, 2001, p.123). Given the promised potential of generative technology, it is paramount that organizations find new ways to develop and sustain their competitive advantage. However, with generative technologies offering nearly limitless potential uses (Constantiou & Kallinikos, 2015; Sandberg, 2014; Vial, 2019; Yoo, 2015), organizations are increasingly challenged to identify suitable applications to match their business needs and enhance their dynamic capabilities. When technology potential is difficult to understand and foresee, it is unclear how organizations should plan and act.

As a result, scholars within information systems (IS) (e.g., Rai et al., 2019; Berente et al., 2019; Coombs et al., 2020) and management theory (e.g., von Krogh, 2018; Raisch & Krakowski, 2020) have called to empirically investigate how organizations understand generative technologies, particularly AI, and use it to adapt, and transform in the face of AI's open-endedness and widespread adoption (Ågerfalk, 2020; Bailey, Faraj, Hinds, Krogh, & Leonardi, 2019; Benbya et al., 2021; Berente, Gu, Recker, & Santhanam, 2019).

This thesis addresses the above calls *by investigating how organizations frame generative AI technology to develop their dynamic capabilities and achieve organizational innovation*. I ground my research in the literature on framing theory and dynamic capabilities. Previous IS management literature highlights the generative nature of AI and the need to understand its characteristics, affordances, and organizational implications proposing framing, i.e., meaning-making processes (Cornelissen & Werner, 2014; Fayard, Gkeredakis, & Levina, 2016; Ivarsson, 2022) as a relevant lens. After all, to harness the promising potential of AI while dealing with its inscrutable nature (Berente, Gu, Recker, & Santhanam, 2021), organizations must find ways to make sense of it and adjust to its non-deterministic outcomes that carry both new challenges and opportunities. Further, the dynamic capabilities lens has gained recent prominence in the IS field as a lens to study how organizations build competitive advantage by means of technology. Thus, integrating concepts from the framing theory and dynamic capabilities literature should provide theoretical explanations for how generative technologies such as AI are understood and leveraged for the development of dynamic capabilities and organizational innovation, an area that remains relatively unexplored within IS (Steininger, Mikalef, Pateli, & Ortiz-de-Guinea, 2022).

To address my research purpose, I conducted two empirical studies. I followed an abductive research approach, and a qualitative multiple-case study methodology to investigate how eight large enterprises implemented a particular low-code, conversational AI (CAI) platform to build CAI applications, such as chatbots and voicebots

In Paper I, I investigate how organizations frame a low-code AI platform to enhance their generative capacity, i.e., the ability to rejuvenate, produce new configurations and possibilities, and challenge the status quo (Avital & Te'Eni, 2009), or simply put, capacity to be creative and think-outside-the-box. Specifically, I focus on how case companies made sense of the low-code AI platform, viewed as a high generative fit platform, and how the platform helped them enhance their generative capacity. My analysis reveals that despite using the same AI platform, only three of the eight case companies were able to enhance their generative capacity. While previous literature argues that high generative fit information systems are more likely to enhance an organization's generative capacity, Paper I demonstrates that this process is not a given. Instead, the process is moderated by carefully crafted tactical framing processes. Additionally, findings suggest major internal and external incongruences. However, contrary to traditional IS view on the implementation-related incongruences highlighted as challenging and undesirable, (Davidson, 2002; Gal & Berente, 2008; Orlikowski & Gash, 1994), Paper I shows that organizations that succeeded the most sought these 'creative conflicts' (Van Burg, Berends, & Van Raaij, 2014; Bumann, 2022) that provided a learning ground and pushed these organizations to reconsider their understanding of the platform and create and employ rhetorical and organizing acts, i.e., tactical framing processes that helped enhance their generative capacity.

Paper II builds on the findings from Paper I and further investigates how the implementation of the low-code AI platform enabled some organizations to develop their dynamic capabilities and achieve organizational innovation, related to "new or altered products, services, processes, systems, organizational structures, or business models" (Mamonov & Peterson, 2021, p. 1). Findings suggest that the AI platform provides a solid foundation for better and more efficient dynamic capability processes of sensing and seizing. The platform enables organizations to quickly capture and obtain a real-time orientation of the unstructured end user data that serves to inform organizations beyond the scope of their current business operations. Specifically, the platform has the potential to enhance managerial cognition by 'signaling' (e.g., detecting customer's demands and the potential action they can instigate) opportunities and threats presented in the user-generated data. However, while helping augment sensing and seizing processes in organizations, the platform only provides an opportunity to transform and innovate. Furthermore, the platform creates a ripple effect of challenges that require new dynamic capabilities. What organizations do with these opportunities and how they deal with the emerging challenges depend on the cognitive and behavioral processes they undertake.

This thesis contributes to the ongoing discourse within the Strategic Information Systems (SIS) literature investigating the implementation of generative technologies and the opportunities they offer for the development of dynamic capabilities and organizational innovation. Taken together, the appended papers refute a common approach to technology implementation that is often measured against a specific and expected outcome. Instead, findings suggest that more open and malleable technologies require more open and flexible cognitive and behavioural processes (e.g., reframing, rhetorical and organizing acts, learning routines) and call for new key performance indicators (KPIs) that can reflect the opportunity-oriented view of technology. The papers also indicate that along with opportunities offered by the generative nature of the platform, organizations are faced with a ripple effect of constrains that require additional dynamic capabilities. This thesis informs practitioners on the cognitive and behavioral processes that facilitate effective implementation of a generative AI platform. It highlights the opportunities and warns about the challenges presented by the platform. Lastly, it suggests that to fully benefit from generative technologies, such as AI, organizations need to reconsider and reframe their narrow and outcome-specific view of technology measured against old KPIs relevant to an outdated functional view on technology.

In the following section, I present in greater detail the literature in which I ground my thesis. After that, I present the methods used in the two appended papers. Lastly, I present and summarize the findings of each paper and discuss theoretical and practical implications, limitations and future research opportunities.

2. Literature review

2.1 Implementation of generative technology

Implementation of new technology in organizations is a complex socio-technical endeavor that "radically changes social structures, culture and processes, and the behavior of actors" (Ngwenyama & Nielsen, 2014). Recent IS literature highlights that large established organizations face more profound challenges when implementing generative technologies in contrast to the entrants, as they have 'more to lose' given the fact they have mature processes, routines, and a collective experience that need to be reconfigured (Ghawe & Chan, 2022) (see Table 1).

Technology implementation is often associated with incongruent views on how and why the technology needs to be implemented. In fact, implementation-related incongruences that stem from misaligned expectations, assumptions, and knowledge bases within and across relevant organizational groups have been used in IS research to explain difficulties associated with technology implementation (Orlikowski & Gash, 1994; Davidson, 2006; Gal & Berente, 2008).

Despite the challenging nature of technology, the previous view of technology as an "engineered artifact, expected to do what its designers intend it to do" (Orlikowski & Iacono, 2001, p. 123) relied on a deterministic nature of technology, viewing it as fixed and immutable (Yoo et al., 2012). This view did not account for generativity, etymologically derived from the verb 'to generate', meaning 'to produce or create' (Thomas & Tee, 2022). In this thesis, I refer to generativity as a technology's capacity to be leveraged across multiple tasks while remaining highly adaptable, accessible, and transferable with the potential to produce "an unprompted change driven by large, varied, and uncoordinated audiences" (Zittrain, 2008, p. 1980). Table 1 provides the main concepts of generativity used in this thesis. It also summarizes the opportunities generativity presents to organizations in general and the challenges related to large organizations in particular.

Main concepts	**Definitions**	**Opportunities**	**Challenges for Implementation in large organizations**
Generativity	technology's capacity to be leveraged across multiple tasks while remaining highly adaptable, accessible, and transferable with the potential to produce "an unprompted change driven by large, varied, and uncoordinated audiences" (Zittrain, 2006, p. 1980).	associated with abundant innovation, new forms of social inquiry, value co-creation; unprompted outcome; incompleteness and thus opportunity for design recombination (Constantiou & Kallinikos, 2015; Vial, 2019; Yoo, 2015; Yoo et al., 2012) technology's incompleteness acts as a trigger for further action and thus exploration of new operational and dynamic capabilities (Garud et al. 2008;	Disrupt legacy systems and processes (e.g., incompatibility of back-end systems to support the front-end of a generative technology) Challenge an established trajectory of performance improvement Challenge existing methods to evaluate performance and redefine what performance means Create potential need for design recombination (e.g., need for additional ML models) that can prolong implementation process with its goals and purpose to remain a continually moving target (Garud et al. 2008) Various interpretations about functionality (due to lack of stability e.g., used for different purposes, change of a core function and features over time) can result in unclear usefulness and change implementation goals

		Steininger et al., 2022)	(Ghawe & Chan, 2022; Kallinikos, Aaltonen, & Marton, 2013)
Generative capacity	an entity's, e.g., community, or an organization ability to rejuvenate, produce new configurations and possibilities, challenge the status quo and help think outside-the-box and imagine the unimaginable (Avital & Te'Eni, 2009)	associated with a potential to produce creative output; challenge assumptions; reframe reality (Avital & Te'Eni, 2009; Thomas & Tee, 2022)	established experiences and ways of organizing can impede • the potential to produce creative output, challenge the assumptions, and reframe reality (Ghawe & Chan, 2022) • an ability to rethink technology's usage and purpose, i.e., 'use recombination' (Henfridsson, et al. 2018)
Generative fit	denotes the extension to which technology can complement, bolster, and enhance the inherent generative capacity of those entities that use it, e.g., community, or an organization (van Osch & Avital, 2010)	associated with modifying capacity to enhance the potential to produce creative output, challenge the assumptions, and reframe reality (van Osch & Avital, 2010)	established experiences and ways of organizing can lead to behavioral rigidity while negatively affecting the extent to which the technology can be reconfigured in the process of implementation (for a better fit) to enhance generative capacity unclear and open-ended potential use of technology can challenge the extent to which the technology can be reconfigured in the process of implementation (for a better fit) to enhance generative capacity (Ghawe & Chan, 2022)

Table 1. Concepts of generativity. Their opportunities and consequences.

The digital innovation literature suggests that the generative nature of digital technology, based on *highly reprogrammable and editable characteristics*, can lead to abundant innovation in different ways (Kallinikos et al., 2013; Yoo, Henfridsson, & Lyytinen, 2010). First, the generativity of digital technologies results in digital trace data that can carry informative insights (Yoo et al., 2012). Contemporary organizations are looking for ways to extract and exploit the potential of these digital trace data. Second, the malleable and dynamic nature of digital technologies, along with digital trace data, can induce new ways of thinking, new ideas, and new understandings of processes (Boland, Lyytinen, & Yoo, 2007). Lastly, generative technology can exhibit a delayed binding of form and function (Yoo et al., 2012; Zittrain, 2008), meaning technology's core functionality and technical capacity can change over time, allowing the realization of new functions and potentials that were not originally accounted for by the designers. For example, a smartphone can change its function over time depending on applications added later (e.g., enabling translation through an app). This delayed functionality and evolving technical capacity make it challenging for organizations to envision the outcome that a technology can generate and impede the common understanding of its anticipated purpose and function, making its implementation all the more challenging.

Moreover, generative technologies *connected and embedded characteristics* make them available across different channels across time and space, thus having a strong effect on end user behavior (Benbya, Nan, Tanriverdi, & Yoo, 2020). First, these characteristics make the end users active participants in a discourse between an organization and its stakeholders. Second, the end users are no longer passive recipients of the products and services that the organizations offer. Instead, they become active participants in what products or services they want to see on the market, making them pull companies in the direction they want the company to go. Due to these connected and engaging digital characteristics, companies have the opportunity to anticipate rather than respond to changes in customer expectations (Vial, 2019).

The concept of generative capacity proposed by Gergen, a social psychology scholar, stems from the notion of generativity (Thomas & Tee, 2022). It is related to the capacity of a subject, e.g., individual, group, organization, "to challenge the guiding assumptions …, to raise fundamental questions …, to foster reconsideration of that which is taken for granted, ... and thereby to generate fresh alternatives for social action" and is considered a source of innovation in itself (Avital & Te'Eni, 2009, p. 348). As further elaborated by the authors (ibid), generative capacity refers to the ability to rejuvenate, produce new configurations and possibilities, challenge the status quo and help think outside-the-box and imagine the unimaginable. The literature indicates that generative capacity is linked to a community of participants, also known as a generative community (Thomas & Tee, 2022) or a generative collective (van Osch & Avital, 2010), whose members have different abilities, access to resources, and perceptions of the world (Thomas & Tee, 2022). This notion provides a logical inference to the idea that generative capacity does not just spark out of nowhere. Rather it emerges through interactions among a heterogeneous range of agents with diverse (Boudreau, 2012) and differentiated (Svahn, Mathiassen, & Lindgren, 2017) skills, expertise, interests, assumptions, and world views. Previous research shows that the more differentiated a community is, the greater the variety of innovation it produces (Spagnoletti, Resca, & Lee, 2015; Svahn et al., 2017).

Generative fit is another concept proposed by IS scholars Avial and Te'Eni (2009). It relates to the design of an IS system, denoting the extension to which technology can complement, bolster, and enhance the inherent generative capacity of those entities that use it, e.g., community, or an organization. Thus, generative fit is understood as an extent to which technology's design (related but not limited to its evocative, engaging, adaptive, and open nature) can instigate the enhancement of generative capacity (van Osch & Avital, 2010). The higher the generative fit an IS system exhibits, i.e., the more evocative, engaging, adaptive, and open it is (van Osch & Avital, 2010), the more promise it holds in enhancing generative capacity. A low generative fit technology is set and normally does not allow its users create anything new. For example, the iPod, a discontinued series of portable media players designed and marketed by Apple, only enabled its users to store and replay digital media files (Avital & Te'Eni, 2009). On the contrary, a high generative fit technology, such as an iPhone, allows third party developers to continue building new applications to augment the phone's existing architecture while enabling its users to access new functions (e.g., translation function).

2.2 Framing theory

The concept of framing has been used across many research domains Framing provides individuals with a lens through which they can see and understand the environment, assess changes in it, and make context-specific interpretations that allow them to make decisions and act (Cornelissen & Werner, 2014).

Orlikowski and Gash (1994) developed the concept of technological frames to account for the specifics of technology and how people understand the nature and role of technology in organizations. Since technology can shape social life while being molded by social and organizational conditions, it is interpretively flexible and therefore open for interpretations across multiple social groups. These diverse and often incongruent interpretations depend on the prior knowledge, experiences, and assumptions that organizational actors have of the technology (Gash & Orlikowski, 1991; Orlikowski, 1992). The socio-cognitive approach to IS research shows that interpretations of technology at the individual and group levels are key to understanding technology's development, use, and change in organizations (Orlikowski & Gash, 1994). Moreover, these meaning-making processes are the building blocks in understanding the organizational impact of new technology (Weick, 1990).

In fact, “construction of meaning” is at the core of framing that helps explain how and why organizational actors “(re)think, (re)interpret, or (re)shape meanings of technologies in a particular organizational context, including their efforts to influence others’ meaning making of technologies” (Ivarsson, 2022, p. 6373). In fact, prior literature on framing covers a range of tactics organizations can use to narrow incongruences and influence creation of a common frame (Ivarsson, 2022).

Given the ever-incomplete (Lehmann, Recker, & Rosenkranz, 2021) and continuously changing scope and capability of generative technology (Coombs, Hislop, Taneva, & Barnard, 2020), it is essential to consider how the meaning-making processes emerge to influence organizational actors’ actions and planned outcomes (Davidson, 2006). Afterall, to maximize generative technology’s potential, organizations must constantly construct and reconstruct their frames, i.e., mental models, by engaging in meaning-making processes of a technology’s evolving features, capabilities, and potentials. Failure to do so, as warned by prior research, can impede the formation of a common mental model and organizational efforts for technology implementation (Leonardi, 2011; Young, Mathiassen, & Davidson, 2016).

Although framing has been recently criticized for being developed in the minds of organizational actors a priori (Gal & Berente, 2008), it should not be confused with ‘priming’. Priming is linked to the framing processes studied at the micro level and is related to the activation of a cognitive frame as a knowledge structure (Cornelissen & Werner, 2014). For example, one might be primed and create an a priori cognitive frame of AI’s full material agency, i.e., “capacity for nonhuman entities to act on their own, apart from human intervention” (Leonardi, 2011), based on the popular discourse and hype around AI. Research clarifies that the framing itself is not constructed a priori at the meso and macro levels, e.g., group or organization. It is rather defined as a meaning-making process that needs to be actively constructed and negotiated through interactive processes of communication by organizational groups in context (Cornelissen & Werner, 2014; Ivarsson, 2022). While ‘priming’ is being set, ‘framing’ is being emergent (Cornelissen & Werner, 2014). Moreover, framing is seen as a broader construct that may incorporate priming (Cornelissen & Werner, 2014).

Framing processes have been investigated at different levels of analysis, such as individual, group, organization, and field (Cornelissen and Werner, 2014). If the first two levels are referred to as the ‘bottom-up’ processes related to how individuals and groups within organizations engage in meaning-making processes and how organizations steer these processes to achieve planned outcomes, the latter two, i.e., organizational and field-level framing imply the ‘top-down’, settled, naturalized, and taken-for-granted schemas of interpretation that provide abstract rules and scripts for appropriate behavior in particular social settings (Cornelissen and Werner, 2014). As a result of the ongoing ‘framing’ and interactions with others, the ‘bottom-up’ processes can extend beyond individual and group levels and form a ‘common ground’ (Berger & Luckmann, 1966, p. 75) of mutual understanding and knowledge that over time can be taken as true and institutionalized.

2.3. Leveraging generative technology: Dynamic Capabilities in IS research

Dynamic capabilities view (DCV) framework emerged in response to criticism of resource-based view of the firm as being ineffective in hyper-competitive environments with rapid changes (Teece, Pisano, & Shuen, 2009). The focal point of DCV is to provide explanations on how organizations react, adapt, and respond to changes in highly volatile environments (Pan, Pan, & Lim, 2015) and how they evolve their resources and capability base over time to ensure sustained competitive advantage (Peteraf, Di

Stefano, & Verona, 2013) through the sensing, seizing, and transforming processes triggered by the opportunities and threats presented in the environment.

The DCV framework has gained prominence in the IS field to explain how organizations leverage technological resources to develop their dynamic capabilities and differentiate their offerings. However, a recent comprehensive critical review of DCV's applications in IS suggests that the role of technology in sustaining and developing dynamic capabilities is still unclear (Steininger et al., 2022). Given the fact that generative technologies can change their core functions and capabilities over time, it's still puzzling how their potential actions, i.e., affordances, can enable the underlying capacities of dynamic capabilities. To date, only a few empirical papers have investigated the interplay between generative technology, i.e., AI, and its impact on the underlying processes of sensing, seizing, and transforming that comprise dynamic capabilities. For example, Mikalef and colleagues (2021) illustrated how AI, within the B2B area, can help organizations monitor customers' preferences more closely (i.e., sense), develop different customer profiles and formulate different ways to promote new products and services (i.e., seize), and lead to the adjustment of their production processes (i.e., transform). Trocin and colleagues (2021) illustrated how AI affordances related to data collection and analysis get actualized and how this process leads to ontological changes in decision-making and provides data-driven legitimization. Shollo and colleagues (2022) illustrated how organizations had to continuously configure and reconfigure their ML applications to match changing conditions of ML value creation and evolving nature of the dynamic capabilities of managing ML applications. The authors stressed the need to develop new dynamic capabilities to sense changes in the environment, assess their impact on the ML effectiveness, and accordingly make necessary changes.

Synthesizing and analyzing the interplay between generative technology and the dynamic capabilities of the firm partially motivates this research for several reasons.

First, organizations turn to generative technologies to attain a wide range of business objectives with a growing number of business activities relying on the action potential (i.e., affordances) of technology (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2012). This means that organizations cannot solely focus on the features closely linked to technology's material properties at the time of implementation in anticipation of a clear outcome. Instead, to achieve the full potential of a generative technology, they must consider the interplay between the technology itself with its highly editable, reprogrammable, and connected characteristics, users with goals, users' capabilities (i.e., how they envision the technology can be used), and the action potential enacted when the technology is put into practice (Stendal, Thapa, & Lanamaki, 2016). The action potential of a technology can thus lead to a myriad of possibilities while putting more pressure on organizations and challenging their ability to react, adapt and respond under high ambiguity and uncertainty posed by the technology itself, i.e., how to plan and act when it is difficult to understand what technology potentials can emerge when it is put into practice?

Second, the evolutionary orientation of DCV can also help explain how organizations adapt and transform in the face of an ever-incomplete (Lehmann et al., 2021) and continuously changing scope and capability of generative technology (Coombs et al., 2020; Shollo, Hopf, Thiess, & Müller, 2022) while learning how to leverage a technology's potential for enhancing dynamic capabilities and achieving organizational innovation (Steininger et al., 2022). Using generative technologies, such as artificial intelligence, can not only help organizations overcome unprecedented environmental challenges, but also reveal some of the IT resources' untapped strengths. As a result, organizations can uncover specific skills and processes acquired and employed while developing an evolving generative technology, which in turn can enable them to develop new capabilities (Salovaara, Lyytinen, & Penttinen, 2019).

3. Methodology

3.1. Research purpose and research questions

Building on the knowledge gaps identified in the previous section, the purpose of this thesis is to investigate and provide new insights on how organizations frame generative AI technology for dynamic capabilities and organizational innovation. The relevance of this research is supported by both theory and practice. Scholars of technology in organizations call for phenomenon-based examination (Bailey, Faraj, Hinds, Leonardi, & von Krogh, 2022; von Krogh, 2018) of AI in organizational settings as the technology is on everyone's agenda, with the IT industry currently leading this 'AI revolution' (Ågerfalk, 2020). From a theoretical standpoint, the IS literature points to an open research area of whether and how leveraging generative technology facilitates the renewal of organizational capabilities and organizational innovation (Steininger et al., 2022) as only a few empirical papers address this knowledge gap (e.g., Trocin et al., 2021; Mikalef et al., 2021). From the practitioner standpoint, while organizations are increasingly adopting AI and using it across a range of tasks, they still only vaguely understand how to implement it effectively and extract value from their investment with many projects not meeting the organization's initial expectations. As such, I developed the following two papers and research questions:

1. Paper 1: How do organizations frame a generative AI platform to enhance their generative capacity?

2. Paper 2: How do organizations develop their dynamic capabilities and achieve organizational innovation using a generative AI platform?

3.2. Research design and setting

This thesis follows a qualitative research approach and employs an abductive research strategy due to the underexplored and poorly defined nature of the phenomenon (Blaikie, 2009; Magnani, 2009). An abductive strategy allows the researcher to move back and forth between the data captured from the language of the social actors and theory while focusing on the discovery of new things, other variables, and new relationships. Rather than confirming existing theory, it focuses on generating new concepts and developing theoretical models (Dubois & Gadde, 2002).

Both papers are based on a multiple-case study approach. I find the multiple-case study approach relevant for the purpose of this thesis as it (1) helps identify and understand the differences and similarities across different organizations in terms of platform implementation (Eisenhardt, 1991; Stake, 1995;), (2) enables the analysis of data across situations as well as within each situation (Yin, 2018), and (3) provides a solid foundation for developing robust and persuasive theories (Eisenhardt & Graebner, 2007; Yin, 2018).

As for the research setting, I chose to investigate the implementation of a low-code conversational AI (CAI) platform in eight large enterprises (all with >5,000 employees; five multinationals and three domestic). The case companies spanned the following industries: Automotive (A), Energy (E), Retail (R), Telecommunications (T), Hospitality (H), Manufacturing (M), with CAI applications implemented for both internal and external operations (Appendix A). The time of platform's use varied from two to ten years. Table 2 provides a brief overview of the case companies.

Name*	Company Description	Time of use
E1	An energy multinational with 80, 000 + employees. Turned to ComVers.AI to discover how they could take advantage of artificially intelligent, humanlike digital employees to transform their customer service.	10 years
A1	An automotive manufacturer with 40, 000 + employees. Implemented ComVers.AI to design a chatbot that can assist in delivering a superior customer service experience while enhancing the customer journey.	3 years
A2	A major European automotive manufacturer with about 50, 000 employees present in 100 countries. Implemented ComVers.AI and deployed CAI applications to support their internal and external business processes.	3 years
R1	An international chain of convenience stores present in 15, 000 + locations with 40, 000 + employees worldwide. Successfully implemented ComVers.AI and deployed CAI applications (voice and chatbots) in only a few months to reduce call volumes to their call centers while delivering 24/7 customer support via CAI.	2 years
R2	A furnishing and home accessories multinational with 70, 000 + employees worldwide. Implemented ComVers.AI and deployed a chatbot for their customer support.	10 years
R3	A European retailer with 20, 000 + employees. Implemented ComVers.AI to deploy a chatbot that would help improve the customer journey.	2 years
T1	A large European telecommunications provider with 2,5 million customers. Implemented ComVers.AI to build its own CAI-enabled platform to design more tailored CAI voice and chatbots.	3 years
H1	A luxury resort located in North America with up to 10, 000 employees. Implemented ComVers.AI to provide unique customer support service.	5 years

Industry: *E - Energy (1 company), A - Automotive (2 companies), R - Retail (3 companies), T - Telecommunications (2 companies), H - Hospitality (1 company).*

Table 2. Overview of the case companies

The research setting was motivated by the fact, that in recent years, organizations have turned to low-code AI platforms to overcome AI's steep learning curve. It is estimated that by 2023 over 50% of medium to large enterprises will adopt low-code as their strategic application platforms (Vincent et al., 2020). Such platforms are characterized by pre-defined components, e.g., AI models, and a graphical user interface that allow non-technical experts to design AI-based applications while making AI and its generative potential more accessible and scalable (Waszkowski, 2019). Their layered, modular, and flexible architecture is expected to fuel generativity while fostering unprompted innovation (Rai, Constantinides, & Sarker, 2019). The AI platforms, including low-code, are here to stay and are expected to change organizations in qualitatively different ways (Holmström, 2021; Sundberg & Holmström, 2022). However, despite the widespread expectation that low-code AI platforms can democratize the implementation of AI while helping organizations rejuvenate and produce new configurations and possibilities, research that covers this context is limited with no understanding of whether these expectations materialize.

The investigated platform is an award-winning AI platform implemented by numerous organizations across Europe, Asia, and North America. I anonymize it as 'ComVers.AI' due to protection of privacy and integrity. The names of the companies and key informants are also anonymized for the same reason. The platform offers multiple languages that make it appealing for multinationals to implement CAI applications, such as chatbots and voicebots, across different markets. The platform is known for its visual and user-friendly interface designed for non-technical audiences, making the implementation of the platform scalable and inclusive. The platform is also known for its AI models that enable companies to develop and optimize their applications whether they have the required input data or not. Specifically, the platform is based on various preset machine learning (ML), natural language processing (NLP), and natural language understanding (NLU) principles to ensure a human-like experience without the need for developers to develop any natural language functionalities to enable language interaction.

As I was investigating how organizations frame generative AI for dynamic capabilities and organizational innovation, I chose this research setting for two reasons. First, I wanted to follow empirical cases of implementation of a generative AI technology within large enterprises to witness how well-established entities with often rigid practices find ways to deal with open, malleable, and open-ended technology while learning how to benefit from it. Second, the chosen platform fits the criteria of a generative technology outlined by Zittrain (2006). It can *leverage a range of tasks*, i.e., it can handle and assist in multiple end user requests while providing human-like answers via text or voice. The platform is *adaptable* as it can be easily modified to broaden its range of uses. For example, the built-in language support in the platform grew from 36 to 84 official languages in fewer than ten years. Due to its low-code capabilities, the platform is *accessible* to a broader audience of non-technical experts. Finally, the platform is highly *transferable*, i.e., changes in the technology can be easily conveyed to others due to its visual interface and API connectivity. Such highly editable and reprogrammable generative characteristics have previously been highlighted (e.g., Yoo, 2010; Kallinikos et al., 2013). The sampling strategy for choosing the eight large enterprises was based on two criteria: (1) the organization's length of time using the platform (from two to ten years) to obtain insights representative of different periods and show whether and how technology's framing and leveraging changed and how it affected the development of dynamic capabilities and organizational innovation, and (2) to ensure heterogeneity across industries.

The two papers are based on the same research setting. Initially, I was interested in investigating how large organizations frame the platform and enhance their generative capacity. Counterintuitive and case-diverse findings of Paper I further sparked an interest to investigate how the case companies differed in terms of how the same AI platform helped them develop their dynamic capabilities and achieve organizational innovation.

3.3. Data collection

"Case study evidence can come from many sources", such as documentation, interviews, archival records, direct observations, participant-observations, and physical artifacts (Yin, 2015, p. 135). As such, the appended papers are based on both primary and secondary data sources (same data sources). Primary data include 24 semi-structured interviews (Table 3). Due to the exploratory nature of the research, interview questions were broad and covered an array of inquiries. These questions comprised the initial expectations and knowledge about the platform, both at the individual and organizational levels, the anticipated and unanticipated outcomes for organizations, the challenges and opportunities organizations came across during the implementation, and the overall effect the platform had on organizations. Examples of interview questions can be found in Table 4. The length of the interviews varied between 40 and 120 minutes, with an average time of 60 minutes per interview. Interviews included persons from different professional backgrounds based on their knowledge and involvement with the ComVers.AI platform: IT front-end and back-end developers, business developers/domain experts, business unit managers, and computational linguists. In addition to the informants from the different case companies (19 in total) who provided insights on the features, implementation, and use of ComVers.AI, I interviewed two third-party computational linguists and a conversational user interface developer working with similar platforms and applications to triangulate my understanding and findings regarding generative low-code AI. Moreover, I interviewed two former employees of the ComVers.AI vendor company to gain insights on the generative nature of the platform and its applications.

Material	Key informants
30 semi-structured interviews	• 19 informants from 8 large enterprises (5 multinationals, 3 national) that adopted ComVers.AI • 2 former employees of ComVers.AI vendor company with knowledge of ComVers.AI capabilities • 2 independent computational linguists and 1 conversational UI developer working with similar CAI tools and applications
Pages	350

Table 3. Overview of primary data sources

Inquiries	Examples of questions
Context background	• Could you please tell me about your company and its main offerings? • Why did your company decide to adopt the platform? Why ComVers.AI? • What does the platform help achieve? What features of the platform does your company benefit from the most? • How the use of the platform affects your business operations? Can you give an example? • Could you tell me about your role and involvement with the platform? How long have you been involved in the implementation/use of the platform? What are your main tasks and responsibilities in relation to platform implementation/use? Did these tasks/responsibilities change over time? How and why? • What did you know about the platform prior to its implementation? Where did you get this information from? How did you get to know about its features? • What expectations did you have from the platform? Did these expectations realize/change over time? Why? • What is AI for you? How do you understand it in the business context of your organization? • From your involvement with the platform, what does it depend upon the most? Does it create any dependencies? What are they?
Implementation and use of the platform	• Could you describe, in as much detail as possible, how the implementation of the platform evolved and how you have worked with it? Who else was involved in the process? • Can you recall any challenges associated with the implementation process? Were there any challenges when you started using the platform? What were they? What did you do to counter them? Who else was involved in this process? • Were there any unexpected benefits your realized after platform's implementation? During the use of the platform? • Were there any deviations from the original plan of implementing the platform? Why? How did you go about it?
Questions about the data	• Did the platform enable the capture of data? What type of data? • How do you work with these data? How do you make sense of it? What do you use these data for? How does your company use these data? • What are the main challenges you face when working with data? How do you overcome them?

Table 4. Excerpt of the semi-structured interview guide

To triangulate my findings, I complemented primary data sources with archival data on the case organizations, such as presentations on CAI expectations and benefits, press releases from the case companies about CAI and ComVers.AI, and publicly available articles on the implementation of CAI from the case companies (Table 5).

Material	Number of documents	Number of pages
• Use-cases – companies implementing ComVers.AI • Internal presentations from case companies • Press releases • Public articles about ComVers.AI • Webinars with case companies and ComVers.AI vendor	20 (including main 8) 3 8 10 3	100 45 10 30 30
	44	215

Table 5. Overview of secondary data sources

3.4. Data analysis

I engaged in a form of grounded theorizing to data analysis (Gioia, Corley, & Hamilton, 2013), drawing on qualitative data from multiple cases (Eisenhardt, 1989; Locke, 2007) to understand and explain how large enterprises frame a generative low-code AI platform and leverage its potential while developing their dynamic capabilities and achieving organizational innovation. After crafting descriptions for each case company (excerpts in the Appendices of the appended papers) (Yin, 2014), I developed the data structure based on iterative sequences of first-order codes, second-order themes, and their aggregate dimensions (Gioia et al., 2013). Initially, I inductively developed the first order codes while looking for patterns in the data that I found interesting, distinguishing between and across cases, or puzzling. In the second step, I developed the second-order themes based on the first-order concepts. I approached the third step of data analysis through abductively moving back and forth between the second-order themes and the appropriate literature or theoretical lens that would help explain the observed patterns in the data.

The grounded theory approach is deemed appropriate due to the under-researched phenomenon and is in line with the abductive research strategy of the thesis. A grounded theory approach to data analysis is also suitable for an IS context concerned with the implementation and effect of novel and poorly understood pervasive digital technologies. Levina (2021, pp. 2–3) states, “If we agree that IS research is research on contemporary phenomena, then we all – whether we are doing quantitative or qualitative scholarship - do some degree of grounded theorizing.”

4. Findings

4.1. Paper I: Enhancing generative capacity through tactical framing: A multiple-case study of an AI platform

This paper investigates how organizations frame the low-code AI platform ComVers.AI to enhance their generative capacity, i.e., ability to rejuvenate, produce new configurations and possibilities, and challenge the status quo. The IS literature indicates that the higher the generative fit of a technology, i.e., an extent to which technology is designed (related but not limited to its evocative, engaging, adaptive, and open nature) (van Osch & Avital, 2010), the more likely it is to enhance generative capacity of the entities that use it e.g., generative community (Thomas & Tee, 2022) and a generative collective (van Osch & Avital, 2010).

Contrary to this expectation, I observed that despite implementing the same platform, labelled as high generative fit, the case companies achieved different outcomes with different levels of generative capacity. While some developed new use cases and functions for the AI platform to perform, others took it even further to rejuvenate their knowledge management systems and expand their business models. For example, E1 implemented 20 more AI-based tools and as a result extended its business model from a product-oriented to a digital service-oriented one, attributing this to platform's implementation. Findings indicate that tactical framing processes, carefully developed and employed by three organizations that succeeded the most, moderated the extent to which a generative fit platform enhanced their generative capacity.

This paper provides several interesting insights contributing to the SIS literature. First, it presents one of the first empirical cases that illustrates how organizations frame a newly implemented high generative fit AI platform to enhance their generative capacity.

Second, Paper I contrasts the traditional view on how implementation-related incongruences can pose challenges to implementation, by illustrating how some organizations learned how to leverage these various perspectives, expectations, and assumptions surrounding the platform and its applications. Findings of Paper I highlight major internal and external incongruences. As a result of the *internal incongruences* between IT and business developers, IT specialists had a realistic view of the platform, whereas business developers expected it to be self-sufficient and covering a wide range of knowledge from the outset. Business developers did not find the platform as easy-to-use and accessible despite the low-code being designed and promoted as such (Waszkowski, 2019). *External incongruences* arose as the end users, e.g., customer service users, viewed the platform's applications and how to interact with them differently. While many engaged in open-ended dialogues with the applications, thereby enabling outside-the-scope insights to be gained through the digital trace data, others were as short as possible and provided almost no information. This made it impossible for the bots to assist with an issue or request subsequently challenging organizations to acquire the needed end-user data. While learning how to overcome these incongruences, three organizations paid attention to these diverse views while seeking ways to benefit from them. This active persuasion of the 'creative conflicts' among a heterogeneous community of IT and business developers, as well as external users resulted in the development and application of *tactical framing processes* that comprised of three *rhetorical acts* and three *organizing acts*. The rhetorical acts are (1) *balanced promotional discourse* pursuing to balance the excitement about the platform and acknowledge its technical limitations, (2) *transparent discourse* informing platform's internal and external users about its current functionalities while highlighting the long-term learning processes required for the platform and applications to become sophisticated over time, and (3) *consistent discourse* in communicating updates and establishing continuous knowledge updates internally and externally about the platform and its applications. Together, these rhetorical acts, i.e., the use of persuasive language with the emphasis on how the discourse around the platform and its applications was presented and handled, helped organizations engage in the creative conflicts around diverse frames and learn how to leverage them.

In addition to the rhetorical acts, three organizations had to rethink and reframe their organizational routines to becoming more (1) *inclusive* to welcome diverse and critical voices about the platform and applications as a way to explore the negative potential outcomes of the technology and identify improvement opportunities. For example, E1 welcomed the doubters of the technology to learn how it could fail in order to create adaptable CAI applications. Organizations also thrived for(2) *agile* to find the best fit of the platform while developing adaptability and openness to change, and (3) *apply inductive approach to data usability* while exploring the end user digital trace data and new ways to repurpose these data in hope to explore other potentials and value creation opportunities. For example, A1 found an opportunity to revive an outdated recycling campaign indirectly solicited by the end users.

Third, findings of Paper I contribute to a more nuanced understanding of the concepts of generative fit and generative capacity. They provide clarity that generative fit, i.e., an extent to which technology is designed to enhance the innate generative capacity, requires support of the tactical framing processes to enhance generative capacity to a higher degree. This is because technology's functionality and process support evolve over time and its design is malleable and adaptive. The platform and its applications are not designed ex-ante. They evolve over time based on newly captured end-user inputs, recently developed, and added ML models that can catch broader end-user intent, etc., meaning the ever-incomplete design of the technology need to be accompanied by the framing processes that would help the community navigate its evolving nature. Our findings also suggest that the 'innate generative capacity' of a community, simply put, capacity to be creative and think-outside-the-box, is not fixed. As the technology evolves and new framing processes are created along the way, the community has an opportunity to enhance its generative capacity through reframing.

Next, building on previous SIS literature, Paper I suggests that an organization's implementation of a generative technology does not enhance its generative capacity unless tactical framing processes are also employed. This paper offers a conceptual framework and two propositions that illustrate the moderating role of tactical framing in the enhancement of an organization's generative capacity when implementing a high generative fit AI platform. The framework provides a starting point to further explore the implementation of high generative fit information systems and the effects of the tactical framing processes on organization's generative capacity.

Lastly, Paper I informs practitioners on the steps that facilitate effective implementation of low-code AI platforms, highlighting that to maximize the full potential of technology and achieve generative capacity, organizations must plan for and organize their rhetorical acts and reconsider and adjust their organizing acts.

At the time of writing this thesis, Paper I is an in-progress manuscript and will be submitted shortly to a relevant IS journal.

4.2. Paper II: How do organizations develop their dynamic capabilities and achieve organizational innovation using a generative AI platform?

This paper investigates how organizations develop their dynamic capabilities using a generative AI platform and achieve organizational innovation.

In this paper, I illustrate that despite the promising potential of AI in general and the low-code platform more specifically, all eight organizations had a very narrow view of the technology, initially perceiving it only as an analytical tool to obtain access to end user data. Of the eight enterprises, six were able to move beyond the narrow, outcome-specific perspective of the platform and its applications and seize opportunities based on the digital trace data created by the end users. They learned that the data collected and combined by the platform could lead to outside-the-scope insights enabling them to renew, improve, or discontinue business services and products. Additionally, findings suggest that three organizations also engaged in major organizational transformations, referring to the platform's implementation as the main driver of this change.

Paper II further indicates that to achieve organizational innovation, organizations need to go through both cognitive and behavioral processes that further develop their dynamic capabilities. The findings highlight the cognitive process of reframing, i.e., a process of looking at old problems in a new light while attacking old challenges with new tactics and experimentation. Findings also highlight the behavioral process of a constant updating of their learning approaches, which resulted in the creation of inclusive, explicit, transparent, and flexible knowledge articulation practices.

In addition to the identified processes that drive dynamic capability development and organizational innovation, Paper II outlines a set of constraints posed by the platform. These constraints signal that despite using a generative technology, organizations appear to still have a very narrow, deterministic view of the technology's outcome and how to measure it. Our analysis also shows that a narrow, outcome-specific view of an AI platform with a potential to contribute to operational capabilities alone is limiting and needs to be reconsidered in order for organizations to fully extract an AI platform's potential.

In relation to the SIS literature, Paper II makes several contributions. First, it contributes to the literature on dynamic capabilities in IS as it discusses how an organization can augment the underlying DC processes of sensing and seizing through the use of a generative AI platform. Second, this paper contributes to our understanding of generative technologies and how they can facilitate organizational innovation. Specifically, it illustrates how organizations adapt and learn how to transform their initial expectations of the technology and its potential outcomes thus extending their cognitive capacity while recognizing the opportunities offered by the platform as a driver of organizational innovation. Third, our findings also refute a common approach to technology implementation that is often measured against a specific and expected outcome. Instead, Paper II suggests that more open and malleable technologies require more open processes of learning and reframing for organizations to maximize the full potential of the implemented generative AI technology.

For practitioners, this paper illustrates how a low-code AI platform can be used as a driver of organizational innovation. Additionally, it illustrates that the implementation of a generative technology with an open-ended value potential requires an organization to constantly reconsider and reframe its understanding of the technology and its outcomes as well as employ more open processes of learning. Paper II suggests that in an attempt to fully benefit from generative technologies, such as AI, organizations need to reconsider and reframe their narrow and outcome-specific view of technology measured against old KPIs relevant to an outdated functional view on technology.

This paper is an in-progress manuscript at the time of writing this thesis. The aim is to submit it to a relevant SIS journal.

5. Discussion

Inspired by recent calls on the nature and management of AI that emphasize the need to investigate how organizations understand AI, adapt, and transform in the face of its open-endedness and widespread adoption (Ågerfalk, 2020; Bailey et al., 2019; Benbya et al., 2021; Berente et al., 2019) and a paucity of empirical research on how generative technology such as AI can be leveraged for organizational innovation (Steininger et al., 2022), I investigated *how organizations frame generative AI technology for dynamic capabilities and organizational innovation*. The two appended papers provide new insights on the challenges, opportunities, and outcomes that arose during the implementation of a low-code AI platform, which I discuss below.

5.1. Framing of generative technology

Framing of a new technology within an organizational context is a dynamic and interpretive process that can be triggered by a variety of organizational circumstances and relies on heterogeneous resources (Davidson, 2006; Ivarsson, 2022). The complexity of this process is often attributed to incongruences, i.e., differences in the content or structure of frames about a technology's development or implementation across groups (Young et al., 2016). These incongruences stem from issues such as misaligned expectations of the nature and outcome of technology and its role within the organization and contradictory actions related to the 'best' implementation practices of involved groups (e.g., IT vs business units), resistance, skepticism, and poor appropriation of technology (Davidson, 2006; Orlikowski & Gash, 1994). The existence of incongruences across relevant organizational groups helps explain difficulties associated with technology implementation (Gal & Berente, 2008; Orlikowski & Gash, 1994).

The appended papers illustrate major incongruences in the understanding of the functioning, evolution, and purpose of the AI platform and its outcomes in the different enterprises.

Previous literature stresses that incongruences, when not framed in a common ground, provide major barriers in a technology's implementation (Gal & Berente, 2008; Orlikowski & Gash, 1994). However, previous studies have mainly investigated the framing processes around *bounded digital technologies with specific functions and outcomes*. Contrary to this, this thesis finds that internal incongruences do indeed need to exist when implementing a generative technology. They seem to support the diversity of knowledge, assumptions, and expectations needed to counterbalance the technology's open-ended nature. The case studies in this thesis illustrate that those organizations that thrived on diversity in their implementation groups, be they domain, culture, gender, or opinion-specific, (i.e., negative view of the platform) were able to frame, challenge, and reframe the common assumptions and understanding of the platform, its applications, and outcomes. By inviting multiple actors with incongruent knowledge, experiences, interests, and views of the technology, organizations are able to detect new and unexpected approaches to the implementation process and reconsider the initially expected outcomes of technology. This finding supports previous literature on innovation and strategic management by showing that knowledge diversity, as a recombination of different kinds of knowledge, is more likely to lead to novel ideas and realizations of unexpected value (Kaplan & Vakili, 2015; van de Ven, 2005).

External incongruences also play an important role as they do not only mirror how the end users perceive the technology and interact with it. When addressed and managed, external incongruences can drive the co-creation of value, allowing organizations to anticipate rather than respond to changes in customer expectations, which has been a strategic imperative for organizations (Vial, 2019). Moreover, as illustrated in Paper II, external incongruences, captured by CAI applications and the platform as digital trace data, provide a breadth of the social inquiries (Constantiou & Kallinikos, 2015; Yoo, 2015).

Given the fruitful nature of external incongruences, Paper II demonstrates how some organizations learned how to manage and benefit from external end user incongruences that led to new use cases and improvement opportunities to their business operations.

In contrast to the commonly held view that implementation-related incongruences are negative and undesirable, this thesis illustrates how some organizations learned how to benefit from the internal and external incongruences associated with the implementation of a generative low-code AI platform. In fact, organizations that succeeded the most in enhancing their generative capacity, developing dynamic capabilities and achieving organizational innovation, sought diversity and thus incongruency to possibly counteract the open-ended nature of a generative technology and allow for a much more dynamic negotiating process with a wide variation of cognitive and behavioral processes that organizations needed to engage in to establish a common ground.

5.2. Leveraging generative technology

The two papers also provide some light on how organizations orchestrated incongruences and learned how to benefit from them by means of *cognitive and behavioral processes*.

5.2.1 Cognitive Processes

The appended papers illustrate the main cognitive process organizations undertook, - *reframing*, i.e., a process of looking at old problems in a new light while attacking old challenges with new tactics. Previous literature indicates that the inability to reframe can impede an organization's learning and creative problem-solving potential (as summarized in Orlikowski & Gash, 1994). Zollo and Winter (2002) suggest that organizational members constantly evaluate their performance in relation to their actions. This cognitive process enables them to enhance their understanding of the causal links, i.e., how their actions affect their performance. I extend this logic to the implementation of generative technologies that can be recombined in a myriad of ways, produce abundant innovations mainly based on digital trace data that can redefine the core characteristics and functions of technology over time, in theory indefinitely (Nambisan, Lyytinen, Majchrzak, & Song, 2017; Yoo et al., 2012). Thus, organizations that implement such technologies need to constantly reflect on their expectations, assumptions, and knowledge about the current and future use of technology with its immediate and latent outcomes. This recursive cognitive process can help extend organizations' cognitive capacity and augment their meaning-making about a new technology and suggest further exploration of its generative potential.

Organizational theory literature indicates that skillful reframing may even form the basis for institutional change (Werner & Cornelissen, 2014). The IS literature highlights that reframing can be necessary if actors find that a newly implemented technology cannot be realized within one frame during development (Ivarsson, 2022). Both papers illustrate how organizations engaged in reframing their initial and incongruent models of the platform, its functioning, evolution, and outcomes. While Paper II covers reframing of the initial expectations around the technology that helped some organizations shift from an outcome-oriented to an opportunity-oriented view of technology, Paper I highlights a similar cognitive process of reframing related to generative capacity and linked to one's ability to deal with unclear tasks, unknown, at least in part, outcomes, with a success criterion on rejuvenation (not efficiency and accuracy) (Avital & Te'Eni, 2009). Such cognitive processes of reframing employed by some organizations helped them rejuvenate their business processes, find new use cases for the platform, and challenge the status quo on how to explore and organize for a more fruitful value-creation process afforded by the platform over time. While cognitive processes are very relevant in the (re)construction of meaning around generative technology, both papers along with prior literature highlight the need to wave in the behavioral processes undertaken by organizations.

5.2.2 Behavioral Processes

The notion of reframing consists of two parts: (1) looking at old problems in a new light while (2) attacking old challenges with new tactics. The papers provide an empirical account of how organizations that succeeded in enhancing their generative capacity, developing dynamic capabilities and achieving organizational innovation, not only looked at old problems anew, but also by what means they actually changed their framing about the technology and its value.

More specifically, Paper I shows how organizations carefully crafted and employed tactical framing processes that became key to achieving high generative capacity by means of rhetorical and organizing acts. Previous literature indicates that carefully crafted rhetoric, i.e., "instrumental use of persuasive language and discourses" (Hsu, Huang, & Galliers, 2014; Ivarsson, 2022), can mobilize support around technology implementation and minimize resistance to change associated with a new technology (Barrett & Walsham, 2013; Werner & Cornelissen, 2014). Recent literature has commented on the power of discursive heterogeneous communities involved in interpretation and use of a generative technology (Thomas & Tee, 2022).

While we observed that organizations promoted the potential of the platform, they were very open about its technical limitations and emphasized the long-term learning and maintenance process required for the platform and its applications to learn over time and become more sophisticated. By putting forward a balanced promotional discourse about the platform, organizations were able to provide discursive justifications that rationalized and legitimized the platform's adoption (Edward, Jr, & Green, 2004). More importantly, such a balanced approach most likely helped demystify the 'black box' of the platform and manage diverse expectations about the functioning, evolution, and purpose of the technology. Literature has shown that an open, diverse community discourse surrounding the implementation of a generative technology cultivates trust and social practices (Faraj, von Krogh, Monteiro, & Lakhani, 2016) and over time can enable community members to reach collective goals through reflection and configuring (Thomas & Tee, 2022).

Additionally, some organizations indicated that their end users were often puzzled about how to use the applications of the platform and what to expect from this human-machine interaction, thus indicating further (external) incongruences. To address this challenge, some organizations established *transparent discourse practices* about the implementation progress internally and how to use it and what to expect from it externally. This tactic helped frame a realistic expectation of the platform and its applications externally, e.g., a chatbot is being transparent on what knowledge base it supports at the moment or a chatbot clearly communicates what recent upgrades it went through to account for the end users' latest questions and recommendations. At the same time, a transparent discourse helped frame the evolving nature of the platform internally, while highlighting it as a learning opportunity that depends on active maintenance and augmentation of its knowledge base over time. Additionally, these organizations pushed for *consistent discourse practices* by establishing internal communication channels for IT and business developers post questions and offer solutions to the implementation and use of the platform as well as encouraging common workshops where heterogeneous knowledge base, assumptions, and expectations could be commonly discussed and challenged. In parallel, through the feedback-loops these organizations gradually informed the end users about recent amendments to the platform and applications.

Among other organizing acts, organizations employed explicit, flexible, and inclusive acts that facilitated organizational learning and knowledge sharing. These practices involved diverse social actors normally gathered in a shared space (e.g., workshops, onboarding sessions) that facilitated reframing through a reciprocal and recursive relationship among discourse, cognition, and action.

6. Limitations and future research

This thesis has several limitations and opportunities for future research. The first limitation relates to the reliance on retrospective data collected from key informants. For example, all interviewed case companies were at different stages of platform implementation. Interviewees described their changing expectations, assumptions, and knowledge of the platform and its applications and how these changed in retrospect. I acknowledge this limitation could be prone to selection bias and recency bias which could impact the data accuracy. However, the research sampling included diverse case companies along a timeline of their engagement with the platform and some internal secondary data to mitigate this limitation. I also attempted to report data collection, procedures, and data abstraction in the most transparent way and presented details of our empirical observations in the papers‘ appendices. Future research could benefit from a single case study following a low-code AI implementation in real-time. This would allow capturing of how organizations engage in the cognitive and behavioral processes and what tactics they employ over time while reframing their understanding of technology with its limitations and potentials. This, however, can be challenging, as the effect might not be evident right away. As this thesis shows, it is often indirect and manifests over time.

Second, this thesis does not provide a nuanced account of the generative capacity realized by some organizations. While I tried to link it to diverse organizational outcomes triggered by the platform implementation and closely link them to (1) an ability to rejuvenate, (2) produce new configurations and possibilities, and (3) challenge the status quo (e.g., update of the knowledge management system triggered by the implementation of the platform and linked to ‘organizational rejuvenation’), a future revision of Paper I will incorporate a more nuanced spectrum perhaps organized around operational efficiency vs. generative capacity of the outcomes.

Third, while this thesis investigates how generative low-code AI platforms help organizations develop their dynamic capabilities and achieve organizational innovation, it only provided a starting point on how generative AI platforms help augment an organization’s sensing and seizing capabilities while providing an opportunity for organizational transformation. Considering the proposed opportunity-oriented view on generative technology in Paper II, future research would require a more nuanced information on the features of a platform, their affordances, their actualization, and their specific outcomes. Thus, future research could separate between a platform’s affordances, use, and outcomes (Leidner, Gonzalez, & Koch, 2018) as when affordances are actualized in use, they can result in different types of uses (actualizations) and outcomes (Mesgari et al., 2018; Steiningner et al., 2022). This would allow to more clearly differentiate technology based on the actions it affords and thus the underlying capacities of dynamic capabilities that it enables to be promising (Steininger et al., 2022). Ethnographic longitudinal studies are also recommended to trace the development of dynamic capabilities based on the open-ended evolution of generative technology. This research approach would help witness and document the development of cognitive and behavioural processes in real time. Moreover, it would help address the lack of attention to the possibility of endogeneity, i.e., possibility of alternative explanations in relating technology to dynamic capabilities (Steininger et al., 2022).

7. Conclusion

Over the last years, scholars in IS (e.g., Rai et al., 2019; Berente et al., 2019; Coombs et al., 2020) and management theory (e.g., von Krogh, 2018; Raisch & Krakowski, 2020) have called to empirically investigate how organizations understand AI technology and adapt and transform in the face of AI's open-endedness (Bailey et al., 2019; Berente et al., 2019; Ågerfalk, 2020; Benbya et al., 2021). In this thesis, I investigated how large enterprises frame and leverage generative low-code AI platform to develop their dynamic capabilities and achieve organizational innovation. I illustrated how organizations that succeeded the most in developing their dynamic capabilities and achieving organizational innovation learned from major internal and external incongruences and carefully crafted and employed tactical framing processes that enhanced their generative capacity. They also learned how to rethink and restructure their cognitive and behavioral processes in order to explore the generative potential of the platform and shift their mindset around the technology from outcome-oriented to opportunity-oriented.

There are two main practical take-aways. First, this thesis shows that organizations still have a very myopic view of the generative technology measuring its performance against old and irrelevant KPIs that are focused on decreasing costs and increasing efficiency. This prevents organizations from looking at the 'horizon of opportunity' that the generative technology can offer. Second, the full effects of AI will not be realized until companies rethink and reframe their understanding of technology that is no magic and constantly evolves and the tactics and routines, they employ. This thesis suggests that more open and malleable technologies require more open processes of learning and reframing for organizations to maximize the full potential of the implemented generative AI technology.

References

Ågerfalk, P. J. (2020). Artificial Intelligence as Digital Agency. *European Journal of Information Systems*, *29*(1), 1–8.

Avital, M., & Te'Eni, D. (2009). From generative fit to generative capacity: Exploring an emerging dimension of information systems design and task performance. *Information Systems Journal*, *19*(4), 345–367.

Bailey, D., Faraj, S., Hinds, P., Krogh, G. Von, & Leonardi, P. (2019). Special Issue of Organization Science: Emerging Technologies and Organizing. *Organization Science*, *30*(3), 642–646.

Bailey, Faraj, S., Hinds, P. J., Leonardi, P. M., & von Krogh, G. (2022). We Are All Theorists of Technology Now: A Relational Perspective on Emerging Technology and Organizing. *Organization Science*, *33*(1), 1–18.

Barrett, M., & Walsham, L. H. and G. (2013). A Rhetorical Approach to IT Diffusion: Reconceptualizing the Ideology-Framing Relationship in Computerization Movements. *MIS Quarterly*, *37*(1), 201–220.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Special Issue Editorial: Artificial Intelligence in Organizations: Current State and Future Opportunities. *MIS Quarterly Executive*, *19*(4), ix–xxi.

Benbya, H., Nan, N., Tanriverdi, H., & Yoo, Y. (2020). Special Issue: Complexity & Is Research Complexity and Information Systems Research in the Emerging Digital World 1. *MIS Quarterly*, *44*(1), 1–17.

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research. *Journal of the Association for Information Systems*, *22*(2), 281–303.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2019). Call for Papers MISQ Special Issue on Managing AI. *MIS Quarter*, 1–5.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing AI. *MIS Quarterly*, *45*(3), 1433–1450.

Berger, P. L., & Luckmann, T. (1966). The Social Construction of Reality: A Treatise in the Sociology of Knowledge. In *Sociological Analysis*.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2012). Digital Business Strategy: Toward a Next Generation of Insights. *MIS Quarterly*, *37*(2), 471–482.

Blaikie, N. (2009). *Designing social research: The logic of anticipation* (Second Edi). Polity Press.

Boland, R. J., Lyytinen, K., & Yoo, Y. (2007). Wakes of innovation in project networks: The case of digital 3-D representations in architecture, engineering, and construction. *Organization Science*, *18*(4), 631–647.

Boudreau, K. J. (2012). Let a thousand flowers bloom? An early look at large numbers of software app developers and patterns of innovation. *Organization Science*, *23*(5), 1409–1427.

Bumann, A. (2022). *NAVIGATING THE BLACK BOX: Generativity and Incongruences in Digital Innovation*.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), 44–57.

Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review. *Journal of Strategic Information Systems*, *29*(4), 101600.

Cornelissen, J. P., & Werner, M. D. (2014). Putting Framing in Perspective: A Review of Framing and Frame Analysis across the Management and Organizational Literature. *Academy of Management Annals*, *8*(1), 181–235.

Davidson, E. (2002). Technology Frames and Framing: A Socio-Cognitive Investigation of Requirements Determination. *MIS Quarterly*, *26*(4), 329–358.

Davidson, E. (2006). A technological frames perspective on information technology and organizational change. *Journal of Applied Behavioral Science*, *42*(1), 23–39.

Dubois, A., & Gadde, L. E. (2002). Systematic combining: An abductive approach to case research. *Journal of Business Research*, *55*(7), 553–560.

E.Stake, R. (1995). The Art of Case Study Research by Robert E. Stake (z-lib.org).pdf. *Sage Publications, Inc.*

Edward, S., Jr, G., & Green, S. E. (2004). A Rhetorical Theory of Diffusion. *Academy of Managemenf*, *29*(4), 653–669.

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. In *The Academy of Management Review* (Vol. 14).

Eisenhardt, K. M. (1991). Better Stories and Better Constructs : The Case for Rigor and Comparative Logic. *Academy of Management Journal*, *16*(3), 620–627.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory Building from Cases : Opportunities and Challenges. *Academy of Management*, *50*(1), 25–32.

Faraj, S., von Krogh, G., Monteiro, E., & Lakhani, K. R. (2016). Online community as space for knowledge flows. *Information Systems Research*, *27*(4), 668–684.

Fayard, A. L., Gkeredakis, E., & Levina, N. (2016). Framing innovation opportunities while staying committed to an organizational epistemic stance. *Information Systems Research*, *27*(2), 302–323.

Gal, U., & Berente, N. (2008). A social representations perspective on information systems implementation: Rethinking the concept of “frames.” *Information Technology and People*, *21*(2), 133–154.

Garud, R., Jain, S., & Tuertscher, P. (2008). Incomplete by design and designing for incompleteness. *Organization Studies*, *29*(3), 351–371.

Gash, D. C., & Orlikowski, W. J. (1991). Changing Frames: Towards an Understanding of Information Technology and Organizational Change. *Academy of Management Proceedings*, *1991*(1), 189–193.

Ghawe, A. S., & Chan, Y. (2022). Implementing Disruptive Technologies: What Have We Learned? *Communications of the Association for Information Systems*, *50*(1), 646–689.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, *16*(1), 15–31.

Henfridsson, O., Nandhakumar, J., Scarbrough, H., & Panourgias, N. (2018). Recombination in the open-ended value landscape of digital innovation. *Information and Organization*, *28*(2), 89–100.

Holmström, J. (2021). From AI to digital transformation: The AI readiness framework. *Business Horizons*.

Hsu, C., Huang, J., & Galliers, R. D. (2014). Conceptualizing the dynamics of rhetorical practice and technological frame in the context of technology diffusion and adoption. *Information and Management*, *51*(8), 984–994.

Ivarsson, F. (2022). Applying Framing Theory in Digital Transformation Research: Suggestions for Future Research. *Proceedings of the 55th Hawaii International Conference on System Sciences*, 6373–6382.

Kallinikos, J., Aaltonen, A., & Marton, A. (2013). The Ambivalent Ontology of Digital Artifacts. *MIS Quarterly*, *37*(2), 357–370.

Kaplan, S., & Vakili, K. (2015). The double-edge sword of recombination in breakthrough innovation. *Strategic Management Journal*, *36*(10), 1435–1457.

Lehmann, J., Recker, J., & Rosenkranz, C. (2021). Designing digital market offerings: how digital ventures navigate the tension between generative digital technology and the existing environment. *MIS Quarterly*, 1–54.

Leidner, D. E., Gonzalez, E., & Koch, H. (2018). An affordance perspective of enterprise social media and organizational socialization. *Journal of Strategic Information Systems*, *27*(2), 117–138.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly: Management Information Systems*, *35*(1), 147–167.

Levina, N. (2021). All Information Systems Theory is Grounded Theory. *MIS Quarterly*, *45*(1), 489–494.

Locke, E. A. (2007). The case for inductive theory building. *Journal of Management*, *33*(6), 867–890.

Magnani, L. (2009). Abduction, Reason and Science: Processes of Discovery and Explanation. In *Kluwer Academic / Plenum Publishers*.

Mamonov, S., & Peterson, R. (2021). The role of IT in organizational innovation – A systematic literature review. *Journal of Strategic Information Systems*, *30*(4).

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital Innovation Management : Reinventing Innovation Management Research in a Digital World. *MIS Quarterly*, *41*(1), 223–238.

Ngwenyama, O., & Nielsen, P. A. (2014). Using organizational influence processes to overcome is implementation barriers: Lessons from a longitudinal case study of SPI implementation. *European Journal of Information Systems*, *23*(2), 205–222. https://doi.org/10.1057/ejis.2012.56

Orlikowski, W. J. (1992). The Duality of Technology : Rethinking the Concept of Technology in Organizations. *Organization Science*, *3*(3), 398–427.

Orlikowski, W. J., & Gash, D. C. (1994). Technological Frames: Making Sense of Information Technology in Organizations. *ACM Transactions on Information Systems (TOIS)*, *12*(2), 174–207.

Orlikowski, W. J., & Iacono, C. S. (2001). Research Commentary: Desperately Seeking the “IT” in IT Research - A Call to Theorizing the IT Artifact. *Information Systems Research*, *12*(2), 121–134.

Pan, G., Pan, S. L., & Lim, C. Y. (2015). Examining how firms leverage IT to achieve firm productivity: RBV and dynamic capabilities perspectives. *Information and Management*, *52*(4), 401–412.

Pavlou, P. A., & Sawy, O. A. E. (2010). The “third hand”: IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, *21*(3), 443–471.

Peteraf, M. A., Di Stefano, G., & Verona, G. (2013). THE ELEPHANT IN THE ROOM OF DYNAMIC CAPABILITIES: BRINGING TWO DIVERGING CONVERSATIONS TOGETHER. *Strategic Management Journal*, *34*, 1389–1410.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next-Generation Digital Platforms: Towar Human-AI Hybrids. *MIS Quarterly*, *43*(1), iii–ix.

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management : the Automation-Augmentation Paradox. *Academy of Management Review*, *46*(1), 192–210.

Roberts, N., & Grover, V. (2012). Leveraging information technology infrastructure to facilitate a firm's customer agility and competitive activity: An empirical investigation. *Journal of Management Information Systems*, *28*(4), 231–270. https://doi.org/10.2753/MIS0742-1222280409

Salovaara, A., Lyytinen, K., & Penttinen, E. (2019). High reliability in digital organizing: Mindlessness, the frame problem, and digital operations. *MIS Quarterly: Management Information Systems*, *43*(2), 555–578.

Sandberg, J. (2014). Digital Capability: Investigating Coevolution of IT and Business Strategies. In *Doctoral Dissertation*.

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals*, *12*(1), 390–439.

Shollo, A., Hopf, K., Thiess, T., & Müller, O. (2022). Journal of Strategic Information Systems Shifting ML value creation mechanisms : A process model of ML value creation. *Journal of Strategic Information Systems*, *31*(3), 101734.

Spagnoletti, P., Resca, A., & Lee, G. (2015). A design theory for digital platforms supporting online communities: A multiple case study. *Journal of Information Technology*, *30*(4), 364–380.

Steininger, D. M., Mikalef, P., Pateli, A., & Ortiz-de-Guinea, A. (2022). Dynamic Capabilities in Information Systems Research: A Critical Review, Synthesis of Current Knowledge, and Recommendations for Future Research. *Journal of the Association for Information Systems*, *23*(2), 447–490.

Stendal, K., Thapa, D., & Lanamaki, A. (2016). Analyzing the concept of affordances in information systems. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *2016-March*, 5270–5277.

Sundberg, L. T., & Holmström, J. (2022). Towards 'Lightweight' Artificial Intelligence: A Typology of AI Service Platforms. *AMCIS 2022 Proceedings*, 0–10.

Svahn, F., Mathiassen, L., & Lindgren, R. (2017). Embracing Digital Innovation in Incumbent Firms. *MIS Quarterly*, *41*(1), 239–253.

Teece, D. J., Pisano, G., & Shuen, A. (2009). Dynamic capabilities and strategic management. *Knowledge and Strategy*, *18*(March), 77–116.

Thomas, L. D. W., & Tee, R. (2022). Generativity : A systematic review and conceptual framework. *International Journal of Management Reviews*, 255–278.

van Burg, E., Berends, H., & van Raaij, E. M. (2014). Framing and interorganizational knowledge transfer: A process study of collaborative innovation in the aircraft industry. *Journal of Management Studies*, *51*(3), 349–378.

van de Ven, A. H. (2005). Running in Packs to Develop Knowledge-Intensive Technologies. *MIS Quarterly*, *29*(2), 365–377.

van Osch, W., & Avital, M. (2010). Generative collectives. *ICIS 2010 Proceedings - Thirty First International Conference on Information Systems*.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, *28*(2), 118–144.

Vincent, P., Natis, Y., Iijima, K., Wong, J., Ray, S., Jain, A., & Leow, A. (2020). Magic Quadrant for Enterprise Low-Code Application Platforms. In *Gartner*.

von Krogh, G. (2018). Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing. *Academy of Management Discoveries*, *4*(4), 404–409. Retrieved from http://journals.aom.org/doi/10.5465/amd.2018.0084

Waszkowski, R. (2019). Low-code platform for automating business processes in manufacturing. *IFAC-PapersOnLine*, *52*(10), 376–381.

Werner, M. D., & Cornelissen, J. P. (2014). Framing the Change: Switching and Blending Frames and their Role in Instigating Institutional Change. *Organization Studies*, *35*(10), 1449–1472.

Yin, R. K. (2014). *Case Study Research, Design and Methods* (Fifth). SAGE Publications, Inc.

Yin, R. K. (2018). Case Study Research and Applications: Design and Methods. In Sixth (Ed.), *Paper Knowledge . Toward a Media History of Documents*. Sage.

Yoo, Y. (2015). It is not about size: a further thought on big data. *Journal of Information Technology*, *30*, 63–65.

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, *23*(5), 1398–1408.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735.

Young, B., Mathiassen, L., & Davidson, E. (2016). Inconsistent and incongruent frames during it-enabled change: An action research study into sales process innovation. *Journal of the Association for Information Systems*, *17*(7), 495–520. https://doi.org/10.17705/1jais.00432

Zittrain, J. L. (2008). *The Future of the Internet* (Vol. 1999). Yale University Press.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, *13*(3), 339–351.