THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Pursuing Value Creation through Low-Code AI:

Sociotechnical Dynamics of Low-Code AI Platform Implementation in Large Organizations

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Abstract

Low-code AI platforms, recognized as *"next-generation"* digital tools, combine AI capabilities with low-code development environments to enable organizations to create AI-based applications that mimic human cognition. By offering features like drag-and-drop interfaces, prebuilt components, and AI-powered functionalities, these platforms simplify development and make advanced AI accessible to a broader audience, including non-technical users. Characterized by generativity, low-code AI platforms hold significant potential for value creation. However, despite their promise, many projects fall short of expectations, often due to implementation challenges and limited understanding of the processes required to realize their transformative potential.

This thesis investigates how large organizations pursue value creation through the implementation of low-code AI platforms and how these platforms influence this process. Based on a qualitative, embedded case study of a specific low-code AI platform that integrates machine learning (ML), natural language processing (NLP), and a low-code (LC) software development environment, this thesis examines how eight large organizations across diverse industries engage in value creation during platform implementation.

Key findings of this thesis are synthesized into a conceptual process model that highlights three adaptation processes that organizations must engage in before value creation can occur: cognitive understanding, contextual adaptation, and infrastructure compatibility evaluation. The model also emphasizes the dual role of low-code AI platforms as: (1) drivers of organizational change, and (2) enablers of data-driven learning and innovation. Finally, the findings caution against a narrow focus on efficiency gains and cost reduction, which are typically associated with low-code AI. Instead, they emphasize the distinction between short-term and long-term value paths.

This thesis responds to calls from information systems (IS) and management scholars for a deeper understanding of low-code AI platforms by addressing gaps in the existing literature. It provides insights into the sociotechnical dynamics underpinning their implementation and offers practical guidance for leveraging their generative potential to drive organizational transformation and long-term value creation.

Key words: *digital platforms, low-code AI platforms, value creation, generativity*

List of Appended Papers

This thesis is based on the following four appended papers:

1. Kandaurova, M. & Bumann, A. (2023). Governance in Implementing Weakly Structured Information Systems. *European Conference on Information Systems (ECIS) 2023 Research Papers.* 354.

2. Kandaurova, M., & Skog, D. A. (2024). Initiating and expanding data network effects: A longitudinal case study of generativity in the evolution of an AI platform. *Proceedings of the 57th Hawaii International Conference on System Sciences (HICSS-57)*: 6250-6259

3. Kandaurova, M., Skog, D. A., & Bosch-Sijtsema, P. (2024). The Promise and Perils of Low-Code AI Platforms. *MIS Quarterly Executive*, *23* (3), 4.

4. Mansoori, Y., Kandaurova, M., & Bumann, A. (working paper). ‘Everyone’ Can Be an Entrepreneur: The Rise of Low-Code/No-Code Entrepreneurship.

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Maria Kandaurova

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1. Introduction

1.1 Research Motivation

Organizations continue to engage in digital transformation to modernize their business processes by adopting powerful technologies. Among these, Artificial Intelligence (AI), defined as *"machines' ability to perform human-like cognitive tasks"* (Benbya, Davenport, & Pachidi, 2020). AI has generated significant excitement in recent years due to its transformative potential and capacity to drive value creation across various industries. As a result, organizations are actively seeking ways to integrate AI into digital applications to automate historically resource-intensive processes (Davenport, 2018), drive innovation, support decision-making, and enable human-like interactions, as exemplified by AI-driven chatbots like ChatGPT (Benbya, Pachidi, & Jarvenpaa, 2021). Despite its promise, realizing AI's potential remains a challenge for many organizations. Key barriers include the technological complexity of AI, arising from its autonomy, inscrutability and learning capacity (Berente, Gu, Recker, & Santhanam, 2021), as well as resource constraints and a shortage of skilled AI expertise. Developing and integrating fully functional AI applications often demands specialized knowledge in areas such as machine learning (ML) and natural language processing (NLP), making AI adoption inaccessible to many organizations.

In response to these challenges, low-code (LC) AI platforms have emerged to transform how organizations develop and implement AI-based applications. Low-code AI platforms simplify the development process by abstracting technological complexity, making it more accessible and scalable for organizations. They achieve this through features such as intuitive drag-and-drop interfaces, pre-built components, and AI-powered capabilities like NLP, image recognition, and predictive analytics. Low-code AI platforms, such as Rasa[1], Kore.ai[2], and Cognigy.AI[3] (Grashoff & Recker, 2024) exemplify this potential, offering AI-driven, low-code solutions that transform organizational functions through task automation, enhanced user engagement, and data-driven decision-making (Benbya et al., 2021). Companies such as IBM, Microsoft, and Oracle are actively integrating low-code features with AI capabilities into their product portfolios (Bock & Frank, 2021) to meet the rising demand for user-friendly AI application development.

Low-code AI platforms are characterized by generativity, as they offer a unique combination of accessibility, adaptability, and leveraging capacity (Kaplan & Haenlein, 2019). These features enable a more heterogeneous group of implementers, including non-technical professionals, to develop AI applications, thereby increasing their potential for unanticipated value creation. However, despite their generative capabilities and widespread promise, significant gaps remain in understanding how these platforms can be implemented effectively to unlock their full value-creation potential.

[1] Design, Review, and Personalize Your AI Assistant as a Team in a Low-Code UI, Rasa, available at: https://rasa.com/product/rasa-x- enterprise/

[2] Acknowledged as the "Future-Oriented Low-Code Multi-Channel Bot Development Platform." See kore.ai for more details.

[3] A low-code development platform for enterprise conversational AI automation.

1.2 Problem Statement

As organizations increasingly adopt low-code AI platforms as an essential element of their *"digital transformation toolkit"* (Carroll & Maher, 2023), specific challenges associated with their implementation persist. While the potential of AI for value creation is widely acknowledged, organizations struggle to realize anticipated benefits. Studies attribute AI's unrealized potential to implementation and restructuring lags (Mikalef & Gupta, 2021), as well as the inherent complexity of AI technologies, which demands specialized expertise in areas like machine learning (ML) and natural language processing (NLP). Although low-code environments aim to address these challenges by offering user-friendly interfaces with drag-and-drop functionality, ease of use alone does not inherently lead to value or democratized AI application development as initially envisioned (Carroll, Holmström, & Matook, 2024; Sundberg & Holmström, 2023). Existing literature on low-code AI platforms primarily focuses on low-code application development processes, offering limited insights into the development of AI-based applications and their end-to-end implementation and integration within organizational contexts (Carroll et al., 2024). As such, many organizations, particularly large ones with legacy systems and established routines (Ghawe & Chan, 2022), face difficulties in leveraging low-code AI platforms effectively.

Furthermore, given that the adoption of low-code AI platforms for developing AI-based applications is still in its early stages and empirical studies remain scarce, further research is needed to understand their impact. In particular, the processes that drive value creation through low-code AI implementation remain poorly understood.

Understanding this phenomenon is both practically and theoretically significant. On a practical level, low-code AI platforms have gained significant attention for their promise of democratizing AI-based application development, making them accessible to non-technical users. This promise has driven substantial market hype, reflected in the rapid growth and adoption of these platforms across industries. For example, according to Gundlapalli, the low-code platform market is expected to grow from \$13.2 billion in 2021 to \$45.5 billion by 2025, reflecting a compound annual growth rate of 28.1%. Gartner further predicts that by 2024, 65% of all software development will occur on low-code platforms (as summarized in Carroll & Maher, 2023). The perceived ease of use and democratizing potential of low-code AI platforms are reinforced by claims that *"the availability of user-friendly, low-code AI could democratize these systems' adoption and stimulate their multidisciplinary use"* (Sundberg & Holmström, 2023, p. 5), while *"transform*[ing] *organizations in qualitatively different ways from other technologies"* (Holmström, 2022, p. 3). However, this optimistic narrative often oversimplifies the capabilities of these platforms, potentially leading organizations to underestimate the complexities of their implementation. Much of the discourse remains conceptual, focusing narrowly on the development phase of low-code applications while overlooking the full lifecycle of implementing and integrating AI-based applications into the business environments they are meant to support. This gap underscores the need for a deeper understanding of the implementation challenges and processes necessary to unlock the transformative potential of low-code AI platforms.

Theoretically, Information Systems (IS) literature predominantly focuses on the implementation of fixed-function technologies with predefined outcomes, leaving the dynamics of implementing adaptive, open-ended systems like low-code AI platforms, characterized by generativity, underexplored (Avital & Te'Eni, 2009; Thomas & Tee, 2022). There is a shortage of empirical studies focusing on the processes that organizations employ in pursuit of value creation when implementing low-code AI platforms. Moreover, existing literature emphasizes the role of platform architecture in enabling generativity through the continuous recombination of modules, leading to unprecedented value paths. However, this perspective often adopts a deterministic view, overlooking the sociotechnical processes and organizational efforts required to realize and sustain such generativity. Building on the sociotechnical perspective of generativity (Thomas & Tee, 2022), this thesis aims to provide a sociotechnical understanding of the facilitative processes organizations employ to pursue value creation when implementing low-code AI platforms. It also evaluates the role of the platform in shaping these processes. This perspective is particularly relevant for AI-based platforms, which, due to their capacity to learn and improve over time, hold unique potential to generate outcomes beyond their original design. Finally, empirical studies on the implementation of low-code AI platforms in the context of value creation, particularly within large organizations, remain limited. This research addresses this gap by offering grounded insights into their implementation, while contributing a much-needed empirical foundation.

1.3 Research Objective and Approach

The aim of this thesis, grounded in a phenomenon-driven problematization approach (Gkeredakis & Constantinides, 2019; Gregory & Henfridsson, 2021; Mathiassen, 2017; von Krogh, 2018), is to investigate the following research questions:

> RQ1: How do large organizations pursue value creation when implementing low-code AI platforms?
>
> RQ2: How does the platform influence this process?

To address these questions, I draw on the concept of generativity as a sociotechnical system, recognizing that low-code AI platforms are characterized by generativity and can therefore fuel value creation. This thesis is based on a qualitative, embedded case study of a low-code AI platform that integrates machine learning (ML), natural language processing (NLP), and low-code software development features to support the creation and deployment of AI-based chatbots and voicebots. Through this case study, the thesis explores how large organizations pursue value creation when implementing and using such platforms. It further identifies and outlines the facilitative processes that enable value creation, highlighting the critical dual role of the platform's generative architecture in shaping and supporting these processes. Insights are developed across four appended papers, which collectively provide a comprehensive view of the sociotechnical dynamics at play.

1.4 Central Argument

The overall argument in this thesis can be outlined as follows:

1. Organizations engage in digital transformation to modernize their business processes through powerful technologies.
2. Artificial Intelligence is one such transformative technology, capable of automating historically resource-intensive processes.

3. As part of these transformation efforts, organizations seek to integrate AI into digital applications to enhance efficiency, innovation, and customer engagement (e.g., AI-driven chatbots like ChatGPT).
4. However, despite AI’s promise, many organizations struggle to fully realize its potential due to key implementation barriers, including technological complexity and the scarcity of specialized expertise.
5. To bridge this gap, low-code AI platforms have emerged to address these challenges by simplifying the development of AI-based applications through user-friendly interfaces, prebuilt components, and AI-powered capabilities.
6. While both low-code development environments and AI technologies are surrounded by significant hype regarding their ability to create value and transform organizations, much of this narrative remains conceptual, offering limited empirical insights into their practical implementation and integration within business contexts.
7. Existing literature provides limited insights into the development of AI-based applications and their end-to-end implementation and integration within organizational contexts using low-code AI platforms.
8. Furthermore, most research focuses on fixed-function technologies with predefined outcomes, leaving the dynamics of implementing adaptive, generative systems like low-code AI platforms underexplored.
9. Understanding these implementation dynamics is essential for uncovering how organizations pursue value creation with low-code AI platforms and how the platforms' anticipated roles support or shape this process.
10. Understanding these implementation dynamics is both practically and theoretically significant.

1.5 Thesis Structure

This thesis is structured as follows:

- Section 2 provides an overview of relevant literature
- Section 3 presents and discusses the research paradigm, design, and setting
- Section 4 provides a summary of the appended papers
- Section 5 presents a discussion in relation to RQ 1 & 2, implications for research and practice, and limitations and future research avenues
- Section 6 presents the conclusion
- The appended papers are presented in full at the end of the thesis

2. Background

2.1 Implementation of Artificial Intelligence (AI) in Organizations

2.1.1 Anticipated Value Creation from AI

Organizations are increasingly implementing AI-based solutions to create value through business process automation, customer and employee engagement, improved decision-making, and innovation (Benbya et al., 2021; Davenport & Ronanki, 2018). These solutions are being implemented in a variety of contexts, ranging from customer service (Schanke, Burtch, & Ray, 2021) and decision-making in healthcare (Lebovitz, 2019) to targeted advertising (Davenport et al., 2020), algorithmic hiring (van den Broek, Sergeeva, & Huysman, 2021), and product development (Recker, von Briel, Yoo, Nagaraj, & McManus, 2023).

Current literature identifies both tangible and intangible dimensions of value created by digital technologies, including AI (Nambisan et al., 2013). Tangible value often refers to economic gains, such as improved operational efficiency, productivity, and cost savings, while intangible value includes enhanced customer satisfaction, improved decision quality, innovation capacity, and even societal benefits. These distinctions underscore the multifaceted nature of value creation, which extends beyond financial outcomes.

The implementation of AI-based solutions is often motivated by the pursuit of economic value through efficiency gains, productivity improvements, and process optimization (Davenport & Ronanki, 2018; Lee, Scheepers, Lui, & Ngai, 2023). This focus on enhancing operational capabilities aligns with a traditional IT-based perspective on value creation, where technology is primarily leveraged to drive measurable performance improvements. However, AI also holds the potential to create other forms of value, such as improving competitive positioning, fostering innovation, and enabling entirely new business models. For example, AI can enhance customer engagement through personalized experiences, enable real-time decision-making in dynamic environments, or support creative processes in product development. While these forms of value may be harder to quantify, they are just as crucial for long-term competitiveness.

Traditional IT-value research focuses on the outcomes of technology implementation, asking questions like, *"What value can AI create for us?"* This outcome-centric perspective often treats technology as a static enabler of predefined objectives. In contrast, powerful digital technologies like AI are inherently dynamic, characterized by generativity, learning, and adaptability (Nambisan et al., 2019). These qualities enable deeper digital transformations that challenge traditional value creation models, which are primarily driven by scale and scope (Baiyere, Grover, Lyytinen, Gupta, & Woerner, 2020). The concept of *"digital X-based value"* (Avital et al., 2019; Baiyere et al., 2020) shifts the focus from viewing value as an inherent feature of technology to understanding it as an emergent outcome of socio-technical enactments. It emphasizes the processes through which value is co-created through the interaction of technology, human actors, and organizational contexts. Questions like *"How do we need to reorganize to create value from AI?"* or *"What processes and capabilities must be in place to unlock AI's potential?"* underscore the importance of understanding the reciprocal shaping between digital technologies and their contextual use, as well as the dynamic, iterative nature of value realization in digital environments. While much of the current research focuses on the economic outcomes of AI implementation, the anticipated value often extends beyond immediate economic gains to include intangible benefits like innovation, employee empowerment, and societal impact. However, these outcomes are difficult to measure and may vary significantly across contexts. For example, while an AI system may deliver operational efficiencies in one organization, its generative capabilities may enable transformative innovation in another (Bailey & Barley, 2020). As a result, defining, verifying, and assessing the value associated with AI remains challenging (Molin et al., 2024). While AI is increasingly implemented to enhance competitiveness and drive innovation across business functions (Davenport & Ronanki, 2018), the existing literature is relatively nascent, with limited empirical evidence on whether and how these outcomes are achieved. There is a need for research that moves beyond outcome-based assessments to explore the processes and organizational changes required to create value from AI.

2.1.2 Challenges of AI Implementation in Large, Well-Established Organizations

Despite the widespread use of AI-based solutions across various contexts, the implementation of AI in organizations, as learning systems (Gregory, Henfridsson, Kaganer, & Kyriakou, 2021) and predictive models (Constantiou, Joshi, & Stelmaszak, 2023), rather than deterministic rule-based expert systems (Gill, 1995), remains a relatively new phenomenon. This evolution reflects the novelty of AI integration into broader organizational and social contexts. Several factors contribute to the limited understanding of the AI implementation process within organizations. The unique characteristics of AI such as *autonomy*, i.e., the ability of an AI system to act without human intervention, *learning,* i.e., the ability of an AI system to improve through data and experience, and *inscrutability*, i.e., the unintelligibility of AI systems to some audiences, given their complex inner workings and probabilistic outputs (Ågerfalk, 2020; Asatiani et al., 2021; Berente et al., 2021) make its implementation different from the implementation of conventional IT systems (Lee, Scheepers, Lui, & Ngai, 2022). This is because AI-based systems rely on inferences, meaning they generate educated guesses or predictions (i.e., probabilistic outputs) by identifying patterns in the data they have learned from (Weber et al., 2022). As a result, their responses may vary even in identical situations, since they adapt based on the specific data and context they are exposed to. Finally, the development of AI systems works from the bottom up, starting from the data and progressing to solutions (Lee et al., 2022) until a desirable performance is reached (van den Broek et al., 2021). Although recent IS literature indicates that new challenges arise from AI implementations urging companies to develop new capabilities (Benbya et al., 2021; Berente et al., 2021; Dwivedi et al., 2021; Weber et al., 2022), scholars and practitioners are still investigating how to effectively integrate AI into organizational processes, reflecting the ongoing evolution of this research area.

Historically, the implementation of new technologies in organizations has been seen as a complex sociotechnical process that *"radically changes social structures, culture and processes, and the behavior of actors"* (Ngwenyama & Nielsen, 2014, p. 205). IS literature has approached this process by dividing implementation into distinct phases, often separated by what is known as the *"implementation line"* (Bailey & Barley, 2020; Leonardi, 2009). Scholars have drawn this line differently, depending on their conceptual perspectives. For example, Cooper and Zmud (1990) introduced a six-stage model of technological implementation, consisting of *initiation, adoption, adaptation, acceptance, routinization, and diffusion*. Similarly, Leonardi and Barley (2010) outlined a model with stages such as *perception, interpretation, appropriation, enactment, and alignment*. More recently, scholars have argued that the implementation of AI-based systems should expand our view beyond the traditional boundaries of the implementation process and consider both the design and use of such technologies in a unified approach (Bailey & Barley, 2020). This perspective challenges the deterministic and linear view of technology, instead recognizing that contemporary technologies infused with AI capabilities offers affordances and constraints (Majchrzak & Markus, 2012) that users can sometimes modify or bypass based on their needs and skills. As a result, *"the same technology can lead to very different and often unanticipated outcomes in different workplaces"* (Bailey & Barley, 2020; p. 5).

Despite multiple views and temporal understandings of the implementation process, IS literature typically characterizes successful implementation as the alignment between organizational goals and the technological or processual elements of the IS in question (Arvidsson, Holmström, & Lyytinen, 2014; Thomas & Tee, 2022). This sociotechnical alignment reflects the dynamic nature of the implementation process where both organizational and technical configurations evolve over time (Saadatmand, Lindgren, & Schultze, 2019).

Viewing IS implementation through the lens of sociotechnical alignment is particularly important for AI-based systems, which must continuously adapt to evolving contextual environments by leveraging ongoing data inputs to refine their outputs and enhance their capabilities (Weber et al., 2022). This adaptive nature underscores that implementing AI-based systems is not merely a technical task but a sociotechnical process that involves aligning technology with organizational practices, user needs, and environmental changes. Effective implementation, therefore, requires strong governance efforts where *“managers negotiate a balance between control and flexibility to afford exploration of digital options”* (Svahn, Mathiassen, & Lindgren, 2017, p. 240).

Recent literature highlights that the implementation of AI-based systems for AI application development poses significant coordination challenges (Grashoff & Recker, 2024), particularly within large, well-established organizations (Ghawe & Chan, 2022). Introducing new technology in such organizations can displace older systems, potentially undermining the value of the firm’s existing knowledge and capabilities. This displacement creates capability gaps for incumbent firms, as they may struggle to adapt to the new technology without sacrificing the expertise built around legacy systems (Svahn, Lindgren, & Mathiassen, 2015). The authors further suggest that *“to successfully pursue digital innovation incumbent firms need to create requisite generative capability. This requires reconfiguration and building of organizational and technological resources to spur the emergence of a seemingly infinite number of product variations and speciations”* (p. 4149). Large, well-established organizations often have deeply ingrained processes, structures, and routines optimized for legacy technologies, making the integration of disruptive AI-based systems particularly difficult. Introducing AI-based systems not only disrupts existing workflows but also requires overcoming organizational inertia, a challenge that is magnified in larger firms accustomed to static and predictable systems (Ghawe & Chan, 2022).

The complexity is further compounded by the need for specialized expertise, such as data scientists, machine learning specialists, and front- and back-end engineers, to build and maintain these systems (Grashoff & Recker, 2024). Despite having the financial capacity to afford such resources, even large organizations often face difficulties in securing the necessary talent (Davenport, 2018; AI Sweden, 2021[4]). Moreover, the development of AI-based applications follows an iterative process involving several crucial steps: preparing input data, refining algorithms, and assessing deployment to ensure the system's outputs align with intended tasks and user requirements (Bumann, 2023). Given the scarcity of in-house expertise to continuously perform these steps, many organizations turn to external vendors offering low-code AI platforms to simplify the implementation process and speed up AI application development (Carroll et al., 2024).

2.2 Low-Code AI Platforms: The Promise to Democratize AI

2.2.1 The Rise of Low-Code AI Platforms

Low-code AI (LC AI) platforms are software development platforms that combine user-friendly, low-code development features with advanced AI capabilities, enabling nontechnical users to create intelligent applications that can perform tasks resembling human cognition (Carroll et al., 2024; Grashoff & Recker, 2024). LC AI platforms are increasingly seen as *"next-generation digital platforms"* that blend ease of use with powerful AI capabilities, empowering a broader range of professionals to develop smarter, more automated applications at scale (Rai et al., 2019). These platforms are expected to democratize the development and use of AI (Sundberg & Holmström, 2023), making AI more accessible to a broader group of developers, including business managers and domain experts interested in automating their tasks and processes. This shift toward *"democratizing AI"* is driven by the need to overcome significant barriers associated with AI deployment, such as the need for specialized coding and design skills (Grashoff & Recker, 2024) due to the inherent complexity and autonomy of AI systems; the demand for integrating diverse data sources to support AI's learning processes; and the inscrutability of AI algorithms (Berente et al., 2021), which makes it difficult for non-experts to understand their intricate workings and outputs. LC AI platforms address these challenges by offering software development environments with intuitive, visual interfaces where users can build applications using drag-and-drop tools and pre-built components, eliminating the need for deep coding skills (Bock & Frank, 2021). The growing belief that these platforms simplify AI development and enable rapid deployment of functional AI applications is gaining traction among managers, reinforced by both vendor marketing and academic research (Grashoff & Recker, 2024; Carroll et al., 2024).

The core characteristics of these platforms related to their low-code software development environments are central to their appeal. These characteristics resemble Zittrain's (2008) features of a generative system. First, *high usability* is central to these platforms, as they provide user-friendly interfaces that enable users without technical expertise to build and modify AI applications. These interfaces typically include visual tools like drag-and-drop functions and pre-built components, allowing users to create complex applications with minimal coding knowledge (Matook, Maggie Wang, Koeppel, & Guerin, 2023). Second, *high integrability* refers to the platforms' ability to seamlessly connect with external data sources and other systems, enhancing the functionality and complexity of AI applications. This is achieved through standardized interfaces, such as APIs, which allow users to *"invoke and integrate external functions"* easily, expanding the platform's capabilities (Bock & Frank, 2021). Finally, *high adaptability* is facilitated by the platforms' modular architecture, often described as consisting of *"Lego bricks"* or *"building blocks."* This design allows for the reuse of development components across different applications, supporting customization and

[4] AI Sweden (2021) [Website] (Retrieved from https://www.ai.se/en/news/addressing-ai-talent-shortage)

enabling users to reconfigure systems to meet specific domain needs. Such adaptability empowers users to translate human knowledge into algorithms, automating processes and enhancing the platforms' versatility (Iho, Krejci, & Missonier, 2021). Together, these characteristics facilitate the development of AI applications and enable seamless data exchange with internal systems and external services, ultimately helping companies automate and enhance resource-intensive processes (see Table 1).

Table 1. *Resolving AI Challenges through Low-Code Platform Features*

Key Activities	Challenges Associated with AI	Characteristics of LC	How LC Features Resolve AI Challenges
Developing AI applications	AI's autonomy and complexity require specialized coding skills and deep technical knowledge. Additionally, the inscrutability of AI algorithms makes it difficult for non-experts to understand and modify AI systems.	LC platforms provide user-friendly, visual interfaces that allow non-technical users to build and modify applications using drag-and-drop functionality and pre-built components. These interfaces minimize the need for traditional coding skills.	**Addressing Autonomy and Complexity**: LC platforms democratize AI development by making the process more intuitive and accessible. Non-technical users can develop AI applications without needing deep expertise in coding or algorithm design, reducing reliance on scarce technical resources. **Addressing Inscrutability**: Visual tools and pre-built components in LC platforms help demystify AI algorithms, making their workings more transparent for non-experts.
Enabling Data Exchange with Internal Systems and External Services	AI's ability to improve through data and experience (i.e., its learning process) requires the integration of diverse data sources, which can be challenging due to the dynamic nature of services and the complexity of legacy systems.	LC platforms support seamless integration with other systems through standardized interfaces like APIs and plugins, allowing for easy access to and the incorporation of external data sources and services.	**Supporting AI Learning:** LC platforms simplify the integration of diverse data sources by offering standardized interfaces like APIs that can easily connect to internal systems and external services, and invoke new functions. This integration capability ensures that AI applications can continuously access the necessary data, enhancing their ability to learn and adapt over time. By removing the technical barriers to data integration, LC platforms make the AI learning process more transparent and less inscrutable.
Automating and Improving Resource-Intensive Processes	Translating tacit, context-specific knowledge into AI algorithms is challenging, as traditional methods often fail to capture the nuanced understanding required for effective process automation. The autonomy of AI systems adds another layer of complexity, as these systems must be capable of making decisions independently while accurately reflecting domain-specific knowledge.	LC platforms offer high adaptability through their modular architecture and libraries of reusable, pre-programmed components. These platforms also feature visual tools that allow domain experts to contribute directly to the development and refinement of AI applications, making AI systems more responsive to specific contextual requirements.	**Enhancing Autonomy and Knowledge Translation:** LC platforms empower domain experts to visually encode their specialized knowledge into AI systems, ensuring that autonomous AI decisions are based on accurate, context-specific information. The visual tools provided by LC platforms make it easier for non-technical experts to contribute their insights without needing to write code, reducing the risk of misinterpretation and capturing the subtle nuances necessary for effective automation. Additionally, the modular nature of LC platforms allows AI applications to be easily updated as new knowledge is gained, ensuring continuous improvement.

Recognizing the demand for accessible AI development, major software vendors such as IBM, Microsoft, and Oracle are incorporating LC features into their AI offerings. For example, Microsoft's Project Bonsai, a low-code AI development platform, accelerates the creation of AI-powered automation to enhance production efficiency. Similarly, mid-sized vendors like

Peltarion AI[5], a digital platform for building, training, and evaluating deep learning models through visual programming, focus on making AI accessible to a wider audience through visual programming, contributing to the growing synergy between LC and AI. Traditional low-code platforms are also integrating AI capabilities, as seen with Mendix's AI-assisted development bots, MxAssist, which provide real-time, context-driven recommendations and automate repetitive tasks like data validation.

Ultimately, the ability of low-code AI platforms to lower the barriers to AI adoption has the potential not only to automate and improve resource-intensive processes through AI-enhanced applications but also to drive significant innovation across industries. By empowering a wider range of users to build AI-enhanced applications, these platforms not only improve operational efficiency but also unlock new opportunities for value creation and business transformation (Carroll & Maher, 2023).

2.2.2 Understanding Low-Code AI Platforms as Weakly Structured Systems (WSS)

Low-code AI platforms can be conceptualized as Weakly Structured Systems (WSS). As outlined by Lyytinen, de Vaujanay, Haefliger, & Fomin (forthcoming), WSS are information systems in which *"functions and what they mean locally as affordances are initially not known – either by the implementers or by the users – and many functions remain equivocal even throughout the use."* (p. 3) With WSS, users discover and define the system's capabilities through continuous interaction and experimentation. A fitting example is the modular architecture of low-code AI platforms, which often come bundled with a library of interfaces like application programming interfaces (APIs) and software development kits (SDKs). Over time, these interfaces can grow in number, extending the platform's functionality and allowing users to continuously uncover new capabilities as they engage with the system.

Unlike Highly Structured Systems (HSS) that are characterized by embedded rules, workflows, and processes that dictate organizational activities, leaving little room for deviation (Fomin, Hammar Wijkmark, & Heldal, 2024; Lyytinen et al., forthcoming), WSS are characterized by flexibility and adaptability and are not governed by centrally imposed organizational rules. Instead, their usage is shaped by local practices and emergent rules that evolve over time as users adapt the system to meet their specific needs. As discussed by Fomin (2024) and Lyytinen and collegues (forthcoming), WSS can be characterized by *affordance ambiguity,* meaning the full range of a WSS's capabilities is not immediately clear and must be discovered through use; *user-driven emergence,* which allows WSS to evolve as users shape the system to fit their tasks, rather than following top-down mandates; *evolution of rules and practices which is dynamic*, with rules emerging from practical use rather than being predefined; and finally, *equivocality of function,* where certain features remain open to multiple interpretations, continually offering new ways for users to apply the system.

2.2.2.1 Contrasting Implementation Approaches in WSS and HSS

The implementation process for Weakly Structured Systems (WSS) differs significantly from that of Highly Structured Systems (HSS) (Eley & Lyytinen, 2023). HSS implementation follows a top-down process aimed at aligning local practices with the system's predefined structure. For example, when a large manufacturing company implements an ERP system like SAP, it comes with pre-configured modules for finance, procurement, inventory management,

[5] Acquired by the video game developer King in 2022

and human resources. The company must adapt its existing processes to fit the rigid structure and workflows dictated by the ERP system. Employees across departments, such as finance or operations, are trained to follow standardized procedures enforced by SAP, ensuring uniformity across business units.

This staged approach of loosening existing practices and rules, introducing new ones, and then solidifying changes (Berente, Lyytinen, Yoo, & King, 2016; Cooper & Zmud, 1990) reflects the deterministic nature of HSS, where the system is seen as an *"engineered artifact, expected to do what its designers intend it to do"* (Orlikowski & Iacono, 2001, p. 123). These systems are designed to standardize operations, improve efficiency, and ensure compliance, offering little flexibility for user interpretation or modification (Berente et al., 2016).

In contrast, WSS are far more flexible and adaptive, allowing users to define their own workflows and practices through continuous engagement with the system, rather than conforming to rigid, predefined processes (Fomin et al., 2024; Lyytinen et al., forthcoming). As a result, the implementation of WSS is typically iterative and emergent, involving ongoing negotiation about how the system will be used in practice. Users discover the system's capabilities and collectively shape its use through a bottom-up process, gradually developing shared practices and norms (Fomin et al., 2024; Lyytinen et al., forthcoming). This emergent approach makes WSS highly responsive and adaptable to the unique demands and contexts of the organizations in which they are deployed. For example, a customer service team in a retail company might decide to implement a low-code AI platform to develop simple chatbots for handling basic customer inquiries, such as order status or product information. Initially, they rely on the platform's drag-and-drop interface to build basic chatbot workflows without needing deep technical expertise, thus accelerating the implementation process. As the team engages with the platform, they gradually explore more advanced capabilities, such as integrating natural language processing (NLP) models or connecting the chatbot to external APIs for real-time inventory updates. The system's modular design allows them to continuously iterate and refine their chatbot, adding new features and adjusting responses based on customer interactions and feedback. This bottom-up process enables users to collectively shape the chatbot's development based on evolving business needs and user behavior. Over time, the team forms best practices around how to design and manage these AI-driven chatbots, and these shared norms influence how future chatbots are developed within the organization. The iterative, emergent nature of this approach makes the platform highly adaptable, ensuring it responds to the unique needs of both the team and the customers they serve, rather than enforcing a predefined, rigid structure.

Fomin et al. (2024) and Lyytinen et al. (forthcoming) provide examples of WSS, such as email, e-learning, and knowledge management systems that support voluntary, flexible, and non-prescriptive organizational tasks such as spontaneous communication, knowledge sharing, and learning. However, WSS are not limited to such examples. Conceptualizing low-code AI platforms as WSS is relevant because it underscores their adaptive and open-ended nature, highlighting how they enable users to innovate continuously, refine their workflows, and collaboratively solve problems without being restricted by rigid, predefined structures. While low-code AI platforms support some of the same tasks as email and e-learning systems, such as communication and knowledge sharing, they extend into areas of process automation, custom workflow design, and dynamic interaction that are not typically covered by systems like email or e-learning. This makes low-code AI platforms not just another form of WSS, but an advanced form that enables organizations to handle more complex, interactive, and automated tasks in addition to the more traditional voluntary and non-prescriptive tasks. While WSS such as knowledge management systems are flexible and user-driven, they are more restricted in scope compared to platforms like Second Life (Wasko, Teigland, Leidner, & Jarvenpaa, 2011) and low-code AI platforms (Carroll et al., 2024; Grashoff & Recker, 2024). These more open-ended systems allow for greater creativity and customization, placing them higher on the WSS spectrum.

The flexibility that defines WSS also presents unique challenges, especially in large organizations. With multiple departments and layers of management, reaching consensus on WSS implementation can be difficult, often leading to inconsistencies in system adoption. The IS literature emphasizes that organizational actors interpret technology based on their prior knowledge, experiences, and assumptions (Gash & Orlikowski, 1991; Orlikowski & Gash, 1992). This diversity of perspectives can complicate the implementation of WSS, which relies on a bottom-up process where both technical and non-technical users must collectively make sense of a system characterized by ambiguous affordances and unclear functions (Volkoff & Strong, 2013). Coordination and communication efforts are further strained, increasing the risk of misalignment and fragmented use of the system. The need for proper governance structures is heightened (Svahn et al., 2017), but the flexibility of WSS complicates the enforcement of consistent practices without stifling innovation. Resistance to change, fueled by established organizational practices and behavioral rigidity, can limit the system's creative potential and adaptability. Moreover, while large organizations may have more resources, effectively coordinating them is challenging given the iterative nature of WSS, which can make the implementation process feel like a moving target with evolving goals. Additionally, integrating WSS with deep-rooted legacy systems adds another layer of complexity, as the flexibility of WSS may clash with the rigid structures of existing systems, requiring careful balancing between openness and control to guide the implementation process and align technological capabilities with organizational goals.

Table 2. *Comparison of WSS and HSS*

Aspect	**Weakly Structured Systems (WSS)**	**Highly Structured Systems (WSS)**
Definition	Systems with minimal predefined rules and structures, offering flexibility and requiring users to define practices and rules over time.	Systems with well-defined, embedded organizational rules and processes that users must follow.
Structure	Open-ended, flexible, and adaptive; users create and discover structures and rules as they use the system. Allow its users to produce generative and creative outcomes (Avital and Te'eni, 2009; Thomas and Tee, 2022)	Rigid, predefined, and standardized; comes with embedded rules and processes that must be adhered to.
Design Focus	Flexibility, adaptability, and the emergence of new practices and innovative outcomes	Standardization, efficiency, and compliance across the organization
Illustrative metaphor	*"empty shells, to be filled later with shared use and related patterns of activity"* (Lyytinen et al., forthcoming)	*"blueprints"* - designed for specific purposes and outcomes, that dictate the structure of organizational activities (e.g., Volkoff et al., 2007)
Implementation Approach	Emergent, iterative, and bottom-up; users explore and gradually formalize practices and rules.	Staged, top-down, and compliance-driven; users must adapt to the system's predefined processes.
User Involvement	High degree of autonomy; users play a significant role in defining how the system is used and integrated into workflows.	Limited autonomy; users must conform to the system's predefined workflows and rules.
Regulatory Process	Practices to rules; users discover affordances and gradually establish shared organizational rules.	Rules to practices; users must align local practices with the system's embedded rules.
Adaptation	Highly customizable; can be adapted to fit various needs and contexts.	Limited customization, often domain specific; designed for specific tasks and processes with little deviation allowed
Examples of Systems	- Low-code AI platforms - E-Learning systems, email, knowledge management systems - Virtual Worlds such as Second Life - Industrial Internet of Things (IIoT)	- Enterprise Resource Planning (ERP) systems (e.g., SAP, Oracle) - Customer Relationship Management (CRM) systems (e.g., Salesforce) - Process Management Systems
References	Grashoff & Recker, 2024; Lyytinen et al., forthc.; Fomin et al., 2024; Wasko et al., 2011; Eley & Lyytinen, 2023	Berente et al., 2016; Berente et al., 2019; Boudreau & Robey, 2005; Lyytinen and Newman, 2015
Examples of Use Cases	- Building customizable chatbots (low-code AI platforms) - Hosting virtual conferences and network events (Second Life)	- Managing customer relationships and sales processes with Salesforce - Automating business workflows with BPM systems
Challenges in Large Organizations	- Requires active user engagement and ongoing adaptation - Governance and regulation need to emerge over time - Implementation can be prolonged due to the need for ongoing adaptation and negotiation.	- Can be inflexible and difficult to adapt to specific needs and contexts - May face resistance from users due to rigid processes - Implementation can be costly and time-consuming

2.3 Generativity as a Sociotechnical System

2.3.1 The Concept of Generativity

Generativity, broadly understood as a system's capacity to produce new and innovative outcomes beyond its original design, has increasingly been used to explain open digital innovation dynamics (Thomas & Tee, 2022), particularly the ones that drive the evolution of digital platforms (Eck, Uebernickel, & Brenner, 2015; Sun, Xu, & Karanasios, 2023). The IS literature emphasizes that generative technologies offer multiple value paths and serve as building blocks for digital innovation (Henfridsson, Nandhakumar, Scarbrough, & Panourgias, 2018). Therefore, this concept is particularly relevant for explaining how large organizations pursue value creation when implementing low-code AI platforms and how the platform's generative architecture influences this process.

Despite being widely discussed as a driver of digital innovation in digital platform ecosystems (Sun et al., 2023; Yoo, Boland, Lyytinen, & Majchrzak, 2012), generativity lacks a singular definition. Instead, the IS literature identifies multiple forms of generativity and their interdependent dynamics (Azad & Faraj, 2011; Thomas & Tee, 2022; Yoo, Henfridsson, & Lyytinen, 2010). One perspective views generativity from a product standpoint, where, for example, a platform's generative architecture can *"enable unbounded growth of new components that expand the product boundaries of a platform beyond its initial conception and further attract more users"* (Fürstenau, Baiyere, Schewina, Schulte-Althoff, & Rothe, 2023; Ghazawneh & Henfridsson, 2013; Henfridsson & Yoo, 2014; Um, Yoo, Wattal, Kulathinal, & Zhang, 2013). Alternatively, generativity can be seen as an outcome that arises from interactions between human actors and technologies (Bygstad, 2017; Staub, Haki, Aier, & Winter, 2022). Finally, following (Yoo, 2013) and his emphasis on a mutually reenforcing and constitutive relationship between social and technological forces for a better understanding of generativity's nature and dynamics, generativity has been conceptualized as a sociotechnical system in which *"social and technical elements interact to facilitate combinatorial innovation"* (Thomas & Tee, 2022, p. 256). Thomas and Tee (2022) provide a more granular outlook on generativity by examining it through an input-process-outcome framework (Sun et al., 2023; Sun, Xu, & Shi, 2022).

The sociotechnical perspective on generativity traces back to Zittrain's foundational work (Zittrain, 2008), where he outlines the key dimensions of generative capacity in technology. According to Zittrain (2008), for a technology to be generative, it must be easily accessible – allowing a wide range of users to access the technology; adoptable (i.e., easy to master according to Zittrain) – capable of being easily used and reconfigured, allowing for broad adoption by different audiences; leveraged – able to handle a variety of tasks, i.e., *"the more a system can do, the more capable it is of producing change"* (p. 71); and adaptable - capable of being built upon or modified to expand its applications. Importantly, Zittrain emphasizes that generative capacity can only be fully realized through human participation, as it is the interactions between people and technology that unlock its potential, since *"as defined by these four criteria, generativity increases with the ability of users to generate new, valuable uses that are easy to distribute and are in turn sources of further innovation*" (Zittrain, 2006, p. 1982; Zittrain, 2008). Thus, generativity is framed not merely as a capacity of technology, but as an emergent property resulting from the dynamic interplay between tools and their users (Zittrain, 2008; Bygstad, 2017).

Building on the sociotechnical perspective, this thesis focuses on the interactions between the generative capacity of technology and the user community, i.e., the implementing organizations, to explore how large organizations pursue value creation when implementing low-code AI platforms and how the platform's generative architecture influences this process. These platforms, conceptualized as weakly structured systems, are characterized by affordance ambiguity, user-driven emergence, and equivocality of function, which reflect the open-endedness and flexibility of the platform's use and its potential for value creation, as users interpret and apply the technology in diverse, often unanticipated ways. However, the ability of low-code AI platforms to function effectively in such environments is closely tied to their generative capacity (Zittrain, 2008). This capacity is defined by four key features that enable the platform to handle the complexity and variability associated with weakly structured systems. For example, low-code AI platforms are *highly accessible*, as they lower the entry barrier, making it easy for a wide range of users, regardless of technical skill, to access and use AI technologies. They are *highly adaptable*, meaning they allow their users to build on existing functionalities, modify workflows, and combine modules to address a variety of business needs. Low-code AI platforms' *leveraging* capacity refers to their ability to handle diverse tasks, such as automating workflows, analyzing data, or building customer-facing applications. They are also *adoptable* in the sense that they can be easily used and reconfigured, allowing for broad adoption by different audiences.

These generative features work in tandem with the platform's weakly structured nature. The platform's affordance ambiguity and open-endedness enable users to explore new possibilities, while its generative architecture provides the foundational capacities that allow users to innovate, repurpose, and create value in various ways. In this way, the generative capacity of low-code AI platforms provides the foundation for dynamic and emergent value-creation processes, however, it does not guarantee their outcome.

In the context of low-code AI platforms, generativity parallels value creation. Digital technologies fueled by generativity *"hold the potential to simultaneously be part of multiple value paths, offered through design recombination* [connecting digital resources as a value offering to users] *and assembled through use recombination* [connecting digital resources in use]" (Henfridsson et al., 2018, p. 89). For instance, a low-code AI platform could be designed with specific modules (design recombination) to automate tasks. However, users in an organization might find ways to apply these modules in entirely new ways to solve different business problems (use recombination). In both cases, the interaction between the social (developers, users, organizational needs) and the technical (platform, data, AI capabilities) drives innovation and value creation, making these processes inherently sociotechnical.

In this view, value creation can thus be conceptualized as an ongoing, dynamic sociotechnical process fueled by the platform's generative architecture and facilitated by the active engagement of its community of users. As the IS literature suggests, the extent to which digital innovation, as a form of value creation, can occur depends on an appropriate combination of a generative technology and the social actors along with their interpretation and use of the technology (Avital & Te'Eni, 2009; Bygstad, 2017). This view on generativity also aligns well with current literature, which describes it in terms of technology and its generative capacity as a function of these capacities, meaning it is not an inherent technological property but something that emerges through use (Zittrain, 2008; Thomas & Tee, 2022).

2.3.2 Generative Capacity: Linking Technological Design to Value Creation

The generative capacity of technology can be understood through the concept of layered modular architecture, commonly used in Information Systems to explain the value-creation potential of digital technologies compared to their non-digital predecessors (Yoo et al., 2010). This section introduces two unique properties of digital technology that enable such generativity: reprogrammability and homogeneity. An illustrative example is a digital camera, which, enhanced with software-based capabilities, can function not only as a camera but also as a video recorder, media player, photo editor, and sharing device. In contrast, a traditional non-digital camera is limited to its original purpose (i.e., taking photos) and cannot evolve beyond that function.

Reprogrammability refers to the ability of digital technology to be modified and repurposed after it has been built and released to the market. Scholars have described this property using terms such as *"flexibility"* (Henfridsson & Bygstad, 2013; Yoo et al., 2012), *"adaptability"* (Zittrain, 2006), *"editability"* and *"reprogrammable"* (Kallinikos, Aaltonen, & Marton, 2013), or being 'plastic' (Bauer, 2014). Regardless of terminology, these concepts emphasize the capacity for new capabilities and functions to be added long after a product's initial deployment (Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015; Henfridsson et al., 2018), a concept Zittrain (2006) describes as *"procrastinated binding of form and function"*. For instance, a company using a low-code AI platform to develop a basic chatbot for customer inquiries can later integrate advanced features such as sentiment analysis by adding AI models or adjusting workflows. This reprogrammability enables the chatbot to evolve and improve without needing to rebuild the system, demonstrating how digital technologies can adapt to changing needs over time.

Regardless of the type of content (e.g., text, images, video, or software code), digital content is stored, transmitted, processed, and displayed in the same fundamental form, encoded as bits of 0s and 1s (Yoo et al., 2010). This uniformity enables seamless interoperability across diverse digital systems. For example, a low-code AI platform for developing chatbots and voicebots can integrate natural language processing (NLP) models (text data), speech-to-text converters (audio data), and UI elements (visual data) within the same development environment. Because all these components share the same digital format, the platform can process them uniformly, facilitating efficient integration and functionality.

Reprogrammability and homogeneity form the foundation for the development of a layered modular architecture (Yoo et al., 2010). This architecture is composed of loosely coupled, modular layers (i.e., devices, networks, services, and content), where innovations or changes can emerge independently in one layer, and these changes can trigger new functions or uses across other layers. This structure creates an environment of open and flexible affordances (Yoo et al., 2012) and thus fosters generativity, i.e., *"a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences"* (Zittrain, 2006, p. 1980). Generativity enables digital technologies to evolve into entirely new capabilities, creating *differences in kind* (i.e., entirely new functionalities or purposes) rather than *differences in degree* (Yoo et al., 2010). For example, a digital camera can function as a video recorder, media player, or photo editor, while a traditional mechanical camera remains limited to its original purpose of taking photos, even with enhancements like a better lens or additional settings.

The four layers of the layered modular architecture represent a stack, where the bottom of the stack corresponds to relatively stable and universally used functions (Hylving & Schultze, 2020). The bottom, or device layer, includes the physical hardware (e.g., computers) and the software that controls it (e.g., operating system). The network layer is the infrastructure that connects devices, whether through physical elements (e.g., fiber optic cables, wi-fi routers) or logical protocols (e.g., TCP/IP protocols that break data into packets and ensure they are transmitted correctly across the network). The service layer *"deals with application functionality that directly serves users as they create, manipulate, store, and consume contents"* (Yoo et al., 2010, p. 727). Key components of the service layer are application programming interfaces (APIs) and software development kits (SDKs) that enable developers to access and integrate various services, tools, and functionalities (such as accessing third-party data, connecting to cloud services, or using pre-built machine learning models) without having to build these capabilities from scratch. The content layer refers to the actual data users create and consume. For example, in the context of low-code AI platforms for AI application development, this could include the user queries and responses generated during chatbot interactions or training datasets for machine learning models. The content layer also encompasses any external data fetched through APIs, like weather data or payment details, that are integrated into the AI application's functionality. The layered architecture allows digital products to have their functionality extended in unexpected ways even after they have been developed and released (Skog, Wimelius, & Sandberg, 2018).

Modularity has come *"to the fore as an important condition for infrastructure evolution"* (Bygstad, 2017) and is key to the layered modular architecture of digital technologies. It *"preserves flexibility within a complex system"* (Baldwin & Clark, 2018, p. 59), allowing distinct and relatively self-sufficient components, i.e., modules, to remain structurally independent of one another, *"within a wider yet loosely coupled network of functional relationships between blocks, mediated through interfaces"* (Kallinikos et al., 2013, p. 360). Saarikko, Westergren, & Blomquist (2020) explain that this loose coupling between components creates conditions for innovation that is less restricted by existing architectural hierarchies and dependencies. Additionally, modularity within each of the above four layers allows for independent modification, recombination, and reuse of digital components, running *"much deeper and wider in digital objects and technologies*" (Kallinikos et al., 2013, p. 360). Modularity provides the possibility to update, replace, or reconfigure different components without requiring changes to the entire layer or system (Yoo et al., 2010). This creates flexibility because developers or users can focus on modifying one part without disrupting the whole. In fact, modularity offers a way to *"preserve flexibility within a complex system"* (Baldwin & Clark, 2018, p. 59). According to Henfridsson and colleagues (2018), layered modular architecture allows digital resources to be flexibly recombined in both design and use, thus leading to multiple value paths. This allows the same digital resource to be a part of multiple value paths, as its meaning and function shift depending on how it is connected with other resources in different contexts. For example, in the context of a low-code AI platform built for the development and deployment of conversational AI-based applications, during the design phase, a developer might combine natural language processing (NLP) model with a sentiment analysis tool to build a customer feedback system for a marketing department. Here, the value path is defined during the design stage, as the combination of these digital resources creates a new solution tailored to marketing. After deployment, an HR department might adapt the same NLP model and sentiment analysis tool for use in employee satisfaction surveys. In this case, the value path is redefined by users who combine the same resources for a different purpose, showing how use recombination can lead to emergent innovations.

The more qualitatively different uses a digital technology can support, the greater its generative potential (Henfridsson et al., 2018). In other words, the greater the flexibility and adaptability of a system, allowing its components to be used in diverse ways and recombined with other resources, the more opportunities it generates for value creation.

3. Methodology

In this section, I present a research paradigm, synthesize the methodological approaches of the appended papers, and provide an overview of the research design that underpins this thesis. I first elaborate on the research paradigm consisting of ontological and epistemological assumptions that align with my beliefs as a researcher about the nature of reality (Levers, 2013), serving as a justification for the selected research design. Next, I outline the reasoning for adopting a qualitative research strategy, and choosing an interpretive, embedded single-case study design as the most suitable approach *to understand and explain how large organizations pursue value creation when implementing low-code AI platforms and how the platform influences this process.*

3.1 Research Paradigm

A research paradigm serves as a broad framework that encompasses a set of assumptions and beliefs about reality, knowledge, and the methods used to study various phenomena. These assumptions are fundamental to all research, as they make complex social phenomena more accessible for investigation. Typically, these assumptions are divided into three key components: *ontology* (the nature of reality), *epistemology* (the nature of knowledge about that reality), and *methodology* (the ways of studying it) (Gioia & Pitre, 1990). Burrell and Morgan (1979) provide a concise classification of these differing assumptions by organizing four distinct research paradigms: (1) interpretive, (2) radical humanist, (3) radical structuralist, and (4) functionalist along two dimensions: objective vs. subjective, and regulation vs. radical change (Gioia & Pitre, 1990).

This thesis adheres to the interpretive research paradigm. This paradigm is characterized by a subjectivist perspective and is focused on regulation rather than change (Gioia & Pitre, 1990). These key characteristics align with the research design of this thesis, which aims to *"generate descriptions, insights, and explanations of events […] so that the structuring and organizing processes are revealed"* (Gioia & Pitre, 1990, p. 588). Moreover, from an interpretive perspective, organizational phenomena, such as the implementation of a new information system or the value-creation processes associated with it, are seen as dynamic, socially constructed, and ongoing. This contrasts with the functionalist perspective, which views such phenomena as stable and objective (Gioia & Pitre, 1990). Below, I elaborate on the ontological and epistemological assumptions that underpin the interpretive paradigm, to which this thesis adheres.

Ontology concerns the nature of reality and the world around us, specifically the part of reality that the researcher chooses to address. It addresses questions about whether reality is an objective or subjective entity, questioning whether it exists independently of human perceptions (realism) or is constructed through human experiences and social processes (constructionism). While constructionism focuses on the individual, emphasizing how people mentally construct their world of experience through cognitive processes, social constructionism shifts the focus to the social level, paying less attention to individual cognitive processes and more to how social interactions shape shared understandings of reality (Andrews, 2012). It emphasizes that our understanding of the world is shaped by social processes, cultural norms, and interactions. Language plays a crucial role in social constructionism, as it helps structure social experiences, and in fact, "*it makes thought possible by constructing concepts"*

(Andrew, 2012, p. 41). According to this perspective, knowledge and meaning are seen as products of these social processes, rather than direct reflections of an objective reality. Consequently, what we consider to be *"real"* in social sciences is heavily influenced by human beliefs, language, and practices (Bastalich, 2015). This thesis adopts a social constructionist approach to examine the experiences and sociotechnical interactions of social actors with a newly implemented LC AI platform.

Epistemology is concerned with what can be known about reality and what types of knowledge are possible. It legitimizes our understanding by questioning how we know what we know. Broadly, epistemology distinguishes between positivism and interpretivism. The positivist approach emphasizes observations, hypothesis generation, testing, and empirical verification of predefined, measurable variables. In contrast, interpretivism focuses on the subjective meaning of social phenomena, positing that knowledge is constructed through social interactions and best understood from the perspective of those involved. While the positivist approach has long dominated the IS field, it has limitations, particularly in accounting for the nuanced ways information systems interact with and are shaped by their context. This limitation is especially evident with flexible and context-agnostic digital technologies, which *"exhibit relations of exteriority"* (Henfridsson et al., 2018 p. 94). In such cases, the meaning and function of digital resources depend on their relationships with other technical or social resources in a given context. Unlike traditional modular systems with fixed component functions, the role and significance of digital resources that are *"emergent by design"* (Nambisan, Lyytinen, Majchrzak, & Song, 2017) can vary widely depending on how they are combined with other resources. This perspective highlights the relevance of the interpretive approach in information systems, which focuses on understanding how people make sense of digital technologies *"through social constructions such as language, consciousness, shared meanings, documents, tools, and other artefacts"* (Klein & Myers, 1999, p. 69). The interpretive approach is particularly well-suited to exploring how these technologies fit into their social and organizational contexts and how they influence and are influenced by these contexts (Walsham, 1995). As the goal of this thesis is to generate insights and explanations of *how large organizations pursue value creation when implementing low-code AI platforms and how does the platform influence this process* – revealing interpretations, meanings, and organizing processes within these organizations – this thesis adopts an interpretive stance.

3.2 Research Design

Methodologically, this thesis adopts a qualitative research approach with an abductive research strategy, allowing for an exploration of social phenomena by moving back and forth between data captured from social actors' language and theoretical frameworks (Blaikie, 2009; Magnani, 2009). This approach emphasizes understanding *"social processes, institutions, discourses or relationships, and the significance of the meanings they generate,"* utilizing methodologies that embrace *"richness, depth, nuance, context, multi-dimensionality, and complexity"* (Mason, 1997, p. 1). It provides a unique capacity to construct compelling arguments about how things work within specific contexts.

This thesis employs an embedded case study methodology (Yin, 2014) to collectively analyze the appended papers. Case study research defines a case as *"the phenomenon that being the focus of interest of the research",* which is *"bound within certain boundaries that have to be specified beforehand in order to help the inquiry over the phenomenon"* (Budiyanto, Prananto,

& Tan, 2019, p. 4). An embedded case study design incorporates more than one unit of analysis, focusing on different units of the case, and thus explicating the evidence through a depth of exploration within various subunits (Scholz & Tietje, 2002). While the common denominator, i.e., the case, across all four appended papers is the low-code AI platform, its generative capacity, and its potential to help large organizations pursue value creation when implementing and using it, individual papers provide insights from different angles. For example, papers 1 and 3 take the 'organization' as the unit of analysis to explore how large organizations pursue value creation when implementing low-code AI platforms. In contrast, papers 2 and 4 focus on the 'platform' as the unit of analysis, offering insights into how the platform's architecture influences this process. Table 3 provides an overview of units of analysis, methods, and data across four appended papers.

Table 3. *Overview of units of analysis, methods, and data across four appended papers*

	Paper 1: Governance in Implementing Weakly Structured Information Systems	**Paper 2:** Initiating and Expanding Data Network Effects: A Longitudinal Case Study of Generativity in the Evolution of an AI Platform	**Paper 3:** The Promise and Perils of Low-Code AI Platforms	**Paper 4:** 'Everyone' Can Be an Entrepreneur: The Rise of Low-Code/No-Code Entrepreneurship
Unit of Analysis	Organization (system implementation)	Platform (ecosystem perspective)	Organization (system implementation)	Platform (artifact perspective)
Method	Case study	Longitudinal case study	Case study	Scoping literature review
Data	**Primary:** semi-structured interviews (40 in total); **Secondary:** blog posts, press releases, presentations, archival data (a lot)			existing literature from relevant fields
Data Analysis	Data structure based on Gioia methodology	Process analysis methods; temporal ordering of key events	Data structure based on open, axial and selective coding	Thematic Analysis

As mentioned above, the focal point of this case study is a low-code AI platform, implemented by eight large, well-established organizations to develop and deploy AI-based applications such as chatbots and voicebots. The embedded case study approach is particularly suitable for summarizing this PhD work for several reasons. First, it provides rich, contextual insights (Yin, 2014) into the development, implementation, and use of the platform within organizations. Paper 2 examines the platform's development from the perspective of the platform developer, offering valuable insights into how the platform's evolving generative capacity is shaped. This perspective helps identify the conditions necessary for the platform to drive generativity and thus potentially lead to value creation within adopting organizations. Similarly, Paper 4 conceptually explores key functional affordances of low-code AI platforms, further enhancing the understanding of their generative capacity and how it may influence the pursuit of value creation. The subsequent papers explore the platform's implementation and use from the viewpoint of adopting organizations. This dual perspective enhances the understanding of the interactions between technology, people, and processes, thereby deepening the contextual understanding of the phenomenon. Second, the embedded case study methodology offers flexibility (Yin, 2014), allowing for adjustments in focus and scope as the study progresses and new insights arise. To secure empirical data during the COVID-19 pandemic, this flexibility was invaluable. It allowed me to adapt to changing circumstances, diversify the research approach and data points, and ultimately enrich the findings. Third, the embedded case study supports the incorporation of multiple data sources (Yin, 2014), such as interviews, observations, documents, and archival records. Relying on both primary and secondary data, this triangulation helped me enhance the validity of the findings. Finally, consistent with my aim to explore and explain how large organizations pursue value creation when implementing and using a new and poorly researched type of digital platform (i.e., low-code AI platform), the embedded case study methodology enabled me to deepen my investigation into new phenomena where little is known; it helped explain the complexities of how and why things happen.

3.3 Research Setting

The research setting of this thesis is a low-code AI platform - CAIP (conversational AI platform)[6] implemented by eight large, well-established organizations from energy (EnerCo), automotive (AutoCo1 and AutoCo2), retail (RetCo1, RetCo2, Retco3), telecommunications (TelCo), and hospitality (HosCo) industries[7]. The selection of this research setting was motivated by two key factors. First, we are witnessing the emergence of next-generation digital platforms powered by AI technologies (Rai et al., 2019). These platforms are equipped with drag-and-drop tools, pretrained AI models, and application programming interfaces (APIs) for services such as vision, speech, language, knowledge, and search (Rai et al., 2019). These capabilities are increasingly offered through low-code software development environments, making advanced AI accessible to a broader range of users without requiring deep technical expertise.

Second, to capitalize on the promise of *"democratizing AI"* (Sundberg & Holmström, 2023), many organizations have turned to AI platforms with low-code development environments to overcome the steep learning curve associated with AI. It is estimated that by 2023, more than 50% of medium to large enterprises will adopt AI platforms with low-code development features as part of their strategic applications (Vincent et al., 2020). These platforms, characterized by predefined components like AI models and graphical user interfaces, enable non-technical users to design AI-based applications, making AI more accessible and scalable (Waszkowski, 2019).

With their modular, layered, and flexible architecture, these platforms are expected to drive generativity and foster value creation for those who implement them (Rai et al., 2019). In fact, they are anticipated to bring about qualitative changes in organizations (Holmström, 2022; L. T. Sundberg & Holmström, 2022). However, despite widespread optimism that these platforms can democratize AI implementation and help organizations pursue value creation, limited research explores whether these expectations are being realized.

This section further elaborates on the studied low-code AI platform and the eight large, well-established organizations that implemented and used it in pursuit of value creation.

[6] The platform has been anonymized, referred to as Comvers.ai in papers 1 and 2, and as CAIP in paper 3. This change was made because, in the later stages of my PhD, an actual platform named Comvers.ai was launched, necessitating the name change to avoid confusion.
[7] The names of the case companies (in parentheses) have been anonymized in accordance with a verbal agreement made before the interviews.

3.3.1 Implemented Low-code AI Platform

The studied low-code AI platform, CAIP, is used by large organizations to develop and deploy conversational AI applications such as chatbots and voicebots. These applications are capable of interacting with humans through text or voice. According to IS literature, conversational AI (CAI) refers to *"a general capability of computers to understand and respond with natural human language as it is written or spoken"* (Benbya et al., 2021, p. 302). This capability depends on the platform's ability to integrate various AI technologies, including natural language processing (NLP), machine learning (ML), automatic speech recognition (ASR), and speech-to-text (STT).

CAIP combines a user-friendly low-code software development environment with advanced AI capabilities, enabling the creation of more intelligent and automated applications. These applications are designed to mimic human cognition, making them accessible to non-technical users. Since its launch in 2012, CAIP has continuously evolved, enhancing both its low-code features and AI capabilities, and thus representing a mature low-code AI platform. Its modular architecture, built around low-code functionality, allows for flexible development and customization. The platform's open-ended design provides a wide range of generic functions, with pre-programmed components and a graphical user interface that simplifies development for users without extensive programming knowledge. This award-winning platform has been adopted by numerous organizations across Europe, Asia, and North America. Its support for multiple languages makes CAIP especially appealing to multinational companies seeking to implement conversational AI applications in various global markets. Furthermore, CAIP provides modules for storing, analyzing, and visualizing natural language data, such as customer support conversations or online reviews, which further enhances its attractiveness to businesses.

A key strength of CAIP is its intuitive, visual interface designed for non-technical users, which ensures scalability and inclusivity during platform implementation. Furthermore, its robust AI models enable organizations to develop and optimize applications regardless of whether they have pre-existing data. By leveraging pretrained machine learning (ML), natural language processing (NLP), and natural language understanding (NLU) principles, CAIP delivers a human-like interaction experience without requiring developers to manually build these language interaction functionalities.

3.3.1 Implementing Organizations

The case companies (five multinationals and three domestic), as mentioned earlier, come from a range of industries, including automotive, energy, retail, telecommunications, and hospitality. They have implemented conversational AI applications for both internal operations (e.g., IT and HR) and external operations (e.g., customer service). The selection of these companies was based on the following criteria: (1) all companies implemented the same low-code AI platform, CAIP, which is a mature platform with advanced low-code features and AI capabilities; (2) the selected companies are large, well-established companies (10.000 - 80.000 employees), either multinationals or domestic, that utilize varying levels of technical expertise to automate complex, established business processes; (3) these companies are industry leaders and early adopters of low-code AI platforms, providing valuable insights into how large organizations pursue value creation through low-code AI implementations, and how the platform's generative architecture influences this process, an area that lacks robust empirical research. A detailed overview of the companies can be found in papers 2 and 3.

The time of the platform's adoption varied from two to ten years at the time of data collection. Table 4 provides a brief overview of the case companies.

Table 4. *Overview of eight organizations that implemented CAIP*

Name*	Company Description	Time
EnerCo**	An energy company with 90, 000 + employees across 100+ countries. Adopted CAIP to automate customer service support and enhance operational efficiency using AI-powered chatbots	10 years
AutoCo1**	An automotive manufacturer with 30, 000 + employees across 100+ countries. Implemented CAIP to enhance its customer service and sales processes through AI-powered chatbots and voicebots across various channels and languages.	3 years
AutoCo2**	A major European automotive manufacturer with about 50, 000 employees across 100+ countries. Implemented CAIP and deployed CAI applications to automate their internal and external business processes, e.g., HR, IT, customer service.	3 years
RetCo1**	An international chain of convenience stores with 40, 000 + employees spanning 15, 000 + locations worldwide. Implemented CAIP to improve its customer service through task and process automation across several locations and languages.	2 years
RetCo2**	A furnishing and home accessories company with 70, 000 + employees worldwide. It operates in more than 50 countries with hundreds of stores worldwide, serving millions of customers annually. Implemented CAIP to automate customer support.	10 years
RetCo3^	A European retailer with 20, 000 + employees. Implemented CAIP to improve customer support through automation	2 years
TeleCo^	A large European telecommunications provider with 2,5 million customers. Implemented CAIP to build its own CAI-enabled platform to design more tailored CAI voice and chatbots.	3 years
HosCo^	A luxury resort located in North America with up to 10, 000 employees. Implemented CAIP for task and process automation for an ultimate customer support service.	5 years

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

3.4 Data Collection and Analysis

"Case study evidence can come from many sources", such as interviews, documents, archival records, direct observations, participant observations, and physical artifacts (Yin, 2014, p. 133). This thesis draws on a series of primary interviews and secondary data as a baseline for this embedded case study.

The primary data consists of 40 semi-structured interviews (see Table 5 for details), which provided flexibility to explore interviewees' perspectives alongside a set of prepared open-ended questions (Flick, 2014). A combination of purposive and snowball sampling was used. Initially, key participants were selected based on their knowledge of the platform and its capabilities from the vendor's perspective, as well as their expertise in platform implementation from the adopting companies' perspective. Following this, additional interviewees were recruited through recommendations or referrals from the initial participants, using snowball sampling. The interviews involved a range of informants. A total of 25 interviews were conducted with representatives from the adopting companies, including 19 initial interviews and 6 follow-up interviews. Additionally, 6 interviews were held with employees from the CAIP platform provider, 3 with independent computational linguists experienced in similar low-code AI tools and applications, and 6 with third-party partners of the CAIP platform provider. Although the interviews with independent computational linguists and third-party partners of the CAIP platform provider were secondary (i.e., not included in the data analysis), they offered valuable insights that enhanced the overall understanding of the platform.

Table 5. *Overview of primary data sources*

Material	Key informants
40 semi-structured interviews	• 25 interviews (19 initial interviews, 6 follow-up interviews) from the informants of 8 large, well-established companies that implemented CAIP (19 of these interviews informed Paper 1, 13 informed paper 3) • 6 interviews from the CAIP platform's provider company to gain insights into the platform's generative architecture (these interviews informed paper 2) • 3 interviews provided by independent computational linguist working with similar LC AI tools and applications (informed a deeper understanding of the LC tools) • 6 interviews from the partners of the CAIP platform provider (informed a deeper understanding of the studied platform)

The informants of the interviews came from different professional backgrounds based on their knowledge and involvement with the platform: IT front-end and back-end developers, business managers, implementation leads, domain experts from adopting companies, AI experts, and business managers from the CAIP platform provider. The length of the interviews varied between 40 and 120 minutes, with an average time of 60 minutes per interview. All interviews were transcribed using Otter.ai, an AI-powered transcription service that automatically converts audio recordings into text. To ensure the accuracy of the transcriptions, a manual review was conducted by comparing the transcribed text with the original audio files to identify and correct any inaccuracies or missing information. Given the exploratory nature of the research, the interview questions were broad and covered a wide range of topics. For the adopting companies, the interview guide included questions about initial expectations and knowledge of the platform at both individual and organizational levels, anticipated and unanticipated outcomes, challenges and opportunities encountered during implementation, and the overall impact of the platform on the organization. For vendor employees, the interview guide focused on the platform's key capabilities, the development process behind those features, and significant events that reshaped or enhanced the platform's low-code and AI capabilities.

The secondary data consists of publicly-available blog posts, press releases, presentations, data sheets (i.e., documents summarizing a technology's components, specifications, and characteristics), use cases, webinars, articles, and archival data traced through the Internet Archive Wayback Machine (see Table 6 for an overview). The majority of the data was collected using a web scraper, an algorithm designed to navigate websites, gather the required information, and store it in a structured format for further analysis.

***Table 6**. Overview of secondary data sources*

Material	Number of documents	Number of pages
• Use cases of CAIP's implementation and use	20 (including main 8)	100
• Internal presentations	5	45
• Press releases & Blog posts	165 most relevant (out of 509)	~200
• Public articles about CAIP	10	20
• Data sheets on CAIP's technical specifications	16	200
• Webinars with case companies and CAIP vendor	5 (main notes)	15

The appended papers employed various data analysis methods tailored to their specific research purposes and designs. Papers 1 and 3 primarily followed the Gioia methodology (Gioia, Corley, & Hamilton, 2013) for data structuring, while Paper 2 utilized process analysis, and Paper 4 applied thematic analysis. Below, I elaborate on each method.

The Gioia methodology (Gioia et al., 2013) was chosen for Papers 1 and 3 for several key reasons. First, it is well-suited for studies exploring new or poorly understood phenomena, as it helps researchers uncover concepts directly from raw data. Second, Gioia's methodology is particularly effective for examining dynamic processes, as it captures not only static data but also the evolving relationships and interactions among emergent concepts. This approach facilitates the development of grounded theory models that explain how organizational phenomena unfold over time, such as during the implementation process. Finally, the methodology provides a structured approach that ensures qualitative rigor by organizing data into 1st-order concepts (informant-centric codes), 2nd-order themes (researcher-centric concepts), and eventually distilling them into aggregate dimensions. This systematic approach was critical in demonstrating how raw data was transformed into theoretical insights, making it an ideal choice for structuring the data in Papers 1 and 3.

Process analysis methods are particularly suited for longitudinal case studies aimed at developing process theories that explain outcomes in terms of the sequence of events leading to those outcomes (Langley, 1999). This approach focuses on understanding the 'how' and 'why' of evolving phenomena, emphasizing patterns of events over time (Langley, 1999). Consequently, process analysis involves handling large amounts of data that describe *"what happened, who did what, and when,"* focusing on events, activities, and decisions ordered chronologically (Langley, 1999, p. 692). In Paper 2, the process analysis method was used to trace the evolution of the AI platform under study, identifying the key mechanisms driving its development. Although process analysis is highly iterative in practice, it can be approached in three key steps (Langley, 1999), which were followed in Paper 2. The first step involved creating a chronological timeline of key events. Paper 2 utilized Aeon Timeline software to organize data points into discrete events on a visual timeline, with each event documented by a title, summary, date of occurrence, and verbatim description. This structured approach allowed for a clear representation of the platform's evolution and facilitated the identification of critical turning points in its development. The second step involved a deeper analysis of the events, conceptualizing them and detecting various patterns among them, while ultimately leading to a linear sequence of 'phases' that occur over time to produce a given result (Langley, 1999). In Paper 2, this step helped identify major changes to the platform's architecture and trace these changes both backward and forward in time, noticing patterns of sociotechnical interactions between an architectural change, new actions amongst a particular type of ecosystem actor, and new architectural changes.

Thematic analysis is a widely used qualitative analytic method *"for identifying, analyzing and reporting patterns (themes) within data. It minimally organizes and describes your data set in (rich) detail"* (Braun & Clarke, 2006, p. 79). Thematic analysis has been found useful in literature reviews, as it is valuable for making sense of a large domain of research (Roberts et al., 2012). Thematic analysis offers immense flexibility when working with qualitative data. It is a relatively easy and quick method to learn. It can usefully summarize key features of a large body of data, while offering a 'thick description' on the data set. It can highlight similarities and differences across the data set, as well as generate unanticipated insights (Braun & Clarke, 2006, p. 97). In conducting a scoping literature review to map out the functional affordances of low-code/no-code tools in Paper 4, thematic analysis provided a well-established framework of sequential phases for interpreting the data.

In these three data analysis methods, I used ATLAS.ti, a qualitative data analysis software, to deeply engage with the data at a granular level. The software facilitated data organization, enabling me to handle various types of qualitative data, from interview transcripts to video recordings of workshops between the adopting companies and the CAIP platform vendor. ATLAS.ti supported an inductive approach, helping me generate first-order themes, concepts, and aggregate dimensions from the data. Additionally, it allowed me to visualize relationships between codes, themes, and key data segments. For example, to better understand the technical properties of the platform, I utilized word clouds to highlight qualitative aspects related to its generative potential.

3.5 Methodological Limitations & Research Quality

This thesis is not without limitations. While the qualitative research design on which this thesis is based provides in-depth, context-rich insights into the phenomenon, it also presents several challenges, such as issues related to generalizability and ambiguity in data interpretation. Despite these limitations, qualitative research remains a valuable approach for exploring complex, nuanced issues within organizations that cannot be fully addressed by quantitative methods, which primarily focus on the falsification of existing theories rather than the generation of new ones.

The decision to employ a qualitative research design in this thesis was motivated by several factors. First, qualitative research focuses primarily on processes rather than outcomes or products. Second, my primary interest as a researcher was in understanding the *"how"* and *"why"* of the value-creation process through the perspectives of human actors, their understanding of the technology, and their navigation within the sociotechnical context of value creation when implementing a low-code AI platform within their organizational settings. Finally, the inductive nature of qualitative research allowed me to build abstractions, concepts, and theories from detailed observations (Ochieng, 2009).

To address the methodological limitations typically associated with qualitative research, I employed strategies aligned with Lincoln and Guba's (1985) trustworthiness markers. Nearly 40 years ago, in their seminal work on qualitative research, Lincoln and Guba posed the question, *"How can an inquirer persuade his or her audiences (including self) that the findings of an inquiry are worth paying attention to, worth taking account of?"* (1985, p. 290). They argued that the world is socially constructed, and that knowledge should be gathered through naturalistic inquiry, an approach that aligns with the phenomenon-based focus of this thesis. Instead of relying on traditional concepts like internal and external validity, reliability, and objectivity, common in quantitative research, Lincoln and Guba (1985) emphasized the importance of credibility, transferability, dependability, and confirmability as markers of trustworthy qualitative methods.

Credibility is analogous to internal validity in quantitative research and refers to the confidence in the *"truth"* of the findings. It focuses on whether the study accurately represents the participants' experiences and whether the interpretations made by the researcher are believable. To ensure credibility, I followed these key strategies. I examined eight large, well-established companies across different industries to identify both the differences and similarities in their implementation of the platform and pursuit of value creation. I employed data triangulation by collecting information from multiple sources, including interviews with representatives from the adopting companies, CAIP platform vendor employees, platform partners, third-party experts working with similar low-code AI tools, and archival data. This approach allowed me to cross-check and verify the consistency of findings, thereby minimizing the impact of subjective interpretations. I also used methodological triangulation by employing different qualitative methods across the appended papers, enabling comparison and validation of the findings, which strengthened the overall robustness of the conclusions. Additionally, I relied on peer debriefing, engaging with impartial peers to review and challenge the research process, interpretation, and conclusion. I also engaged in reflexive discussions about data coding and interpretation with my co-authors. This collaborative approach helped identify potential biases and areas of misinterpretation, ensuring the overall credibility of the findings.

Transferability refers to the extent to which findings can be applied to other contexts or groups, similar to external validity or generalizability in quantitative research. However, since qualitative research is highly context-specific, the aim is not to generalize across all settings, but to provide sufficient contextual detail for others to determine whether the findings apply to their own situations. In this thesis, the case study approach was not designed to offer broad generalizations, but rather to provide insightful, context-rich accounts (Yin, 2014) of how large organizations pursue value creation when implementing low-code AI platforms, and how the platform's generative architecture influences this process. As Yin (2014, p. 53) emphasizes, case studies are not *"samples"* like in experiments; their purpose is to conduct a *"generalizing"* analysis by extending theoretical propositions through analytic generalizations, rather than generalizing to populations through statistical means. To ensure transferability and address the limitations of generalizability, I triangulated the primary data with a wide range of secondary data sources to enhance the credibility of the findings (Flick, 2014). This methodological triangulation, combining different data sources, led to data saturation, which emerged from the depth of the data rather than the number of interviews alone (Fusch & Ness, 2015). The richness of the secondary data further contributed to a deeper understanding of the case companies' experiences with the CAIP platform, adding valuable nuance and depth to the analysis. Acknowledging the limitation of an imbalanced sample size in the interviews, I ensured the selection of respondents with significant knowledge of the implementation process by using a combination of purposive and snowball sampling. I used different units of analysis across the appended papers, with additional primary and secondary data sources, to deepen my understanding of the studied phenomenon. Although the names of the platform and adopting companies were anonymized in accordance with a verbal agreement made before the interviews, which I chose to honor, I remained transparent about the contextual details of the study. By clearly describing the study's boundaries (e.g., participant characteristics, technical features, and capabilities of the platform, time of implementation) across the appended papers, I trust that readers and future researchers will be able to evaluate where the findings may or may not be applicable.

Dependability, analogous to reliability in quantitative research, refers to the stability and consistency of research findings over time. It ensures that the research process is logical and thoroughly documented, making it traceable. To ensure the dependability of this research while addressing the issue of ambiguity in data interpretation, I carefully documented each stage of the process, including the research purpose, approach, data collection, and analysis, which are detailed in the appended papers. First, I used ATLAS.ti and its data visualization features to explore patterns and relationships within the data at a more granular level, yielding a clearer and more structured interpretation. Second, although I used the AI-based tool Otter.ai for interview transcriptions, I conducted manual reviews to compare the transcriptions with the original audio files, correcting any inaccuracies or missing information. As mentioned earlier, I employed multiple methods, units of analysis, and diverse data sources across the appended papers to verify findings and avoid over-reliance on a single perspective. I ensured coding consistency for the data structure across the appended papers, using a structured and transparent coding framework to systematically analyze the data. Finally, I applied peer debriefing (Flick, 2014) and engaged in reflexive discussions about data coding and interpretation with my co-authors. This collaborative approach helped identify potential biases and areas of misinterpretation, ensuring that the final analysis was more objective and robust.

Confirmability is the qualitative counterpart to objectivity in quantitative research. It refers to the degree to which the findings are shaped by the participants and the data, rather than by the researcher’s biases, motivations, or assumptions. Despite the significant hype surrounding AI and its potential since the start of my PhD, which was further amplified by recent examples of AI-based tools like ChatGPT, Copilot, and Midjourney, which have demonstrated impressive abilities to generate human-like text, images, and videos, I remained committed to the exploratory nature of my research design. To ensure the confirmability of this research, I applied a critical lens to examine the practical implications of AI. I carefully traced the processes and methods across eight large, well-established organizations to assess whether the potential of AI was realized or fell short in practice. A good example of my critical examination is evident in Paper 3, which addresses not only the promise, but also the perils of low-code AI platforms, warning IS researchers and practitioners about the sociotechnical complexities of the implementation and use of such technologies. By staying open to the insights shared during the interviews, I was able to identify and describe several false assumptions held by the interview subjects regarding the promising potential of AI prior to the implementation process. These assumptions, made without a critical examination of whether they would hold true in practice, ultimately limited the potential of both low-code and AI solutions. In addition to reflexivity and a critical examination of the studied phenomenon, I relied on the triangulation of data and methods across the appended papers to ensure that the findings were grounded in the data and not merely the result of the researcher’s perspectives.

4. Summary of Papers

This chapter provides an overview of the four papers appended to this thesis. The description of each paper covers the status/outlet, authors, area of concern, type of paper, type of theoretical explanation, research question, theoretical framing, and relevance to RQ1 and RQ2. Table 7 offers a short summary of the papers.

Table 7. *Overview of appended papers*

	Paper 1: Governance in Implementing Weakly Structured Information Systems	**Paper 2:** Initiating and Expanding Data Network Effects: A Longitudinal Case Study of Generativity in the Evolution of an AI Platform	**Paper 3:** The Promise and Perils of Low-Code AI Platforms	**Paper 4:** 'Everyone' Can Be an Entrepreneur: The Rise of Low-Code/No-Code Entrepreneurship
Status/Outlet	Published/ECIS	Published/HICSS	Published/MISQE	Manuscript/will be submitted
Authors	Kandaurova & Bumann	Kandaurova & Skog	Kandaurova, Skog & Bosch-Sijtsema	Mansoori, Kandaurova & Bumann
Area of Concern	Implementation of weakly structured systems	AI platform evolution through DNEs	Challenges and solutions in the implementation of low-code AI platforms	Affordances of LC/NC platforms for digital entrepreneurship
Type of Paper	Empirical/Academic	Empirical/Academic	Empirical/Practitioner	Theoretical/Conceptual
Type of Theoretical Explanation	Explanatory	Explanatory	Prescriptive	Descriptive
Research Question	*How do organizations' governance practices facilitate alignment between weakly structured information systems' capabilities and organizational goals?*	*How do AI platforms grow and improve their algorithmic capabilities over time?*	*What challenges exist in the implementation of low-code AI platforms and how can organizations overcome these challenges?*	*What functional affordances do LC/NC platforms offer, and what opportunities and constraints do they present for different venture creation processes in digital entrepreneurship?*
Theoretical Framing	Generative Governance	Data Network Effects (DNEs)	Generativity	Technology Affordances
Each paper in relation to RQ1 and RQ2				
RQ1*	X		X	
RQ2**		X		X

*RQ 1: How do large organizations pursue value creation when implementing low-code AI platforms?
**RQ2: How does the platform influence this process?

4.1 Paper 1

Kandaurova, M. & Bumann, A. (2023). *Governance in Implementing Weakly Structured Information Systems.* European Conference on Information Systems (ECIS) 2023 Research Papers. 354.

Paper 1 explores and explains governance practices in the implementation of weakly structured information systems (IS). Unlike highly structured systems like ERP, which embed clear organizational rules in their design, weakly structured systems, such as low-code platforms, are open-ended and adaptive. They enable a wide range of functions and applications, allowing users to create generative outcomes. The open-ended nature of weakly structured systems complicates implementation and requires a deeper understanding of governance practices to align social and technical aspects effectively. While research on implementing highly structured systems is extensive, little is known about implementing weakly structured systems. This paper explores: *What governance practices do organizations enact during the implementation of weakly structured information systems? How do these practices facilitate the alignment between technological capabilities and organizational goals?*

Theoretically, this paper draws on the concept of generative governance (Thomas & Tee, 2022), to investigate the governance practices organizations employ during the implementation of a weakly structured system. Empirically, following a case study methodology, it focuses on the implementation of a low-code AI platform by eight large, well-established companies from various industries, including automotive, energy, retail, telecommunications, and hospitality.

The findings reveal significant differences in adoption goals and outcomes across the eight companies, despite using the same low-code AI platform. While some companies successfully integrated the platform to enhance business processes and expand their dynamic capabilities, others encountered technical difficulties that impeded efforts to improve operational efficiency. These differences are attributed to the governance practices each organization employs to align their goals with the platform's open-ended capabilities. Organizations with better alignment exercised key access practices by promoting diversity within their implementation teams and ensuring strong team commitment. They also imposed effective control practices through a combination of technical, economic, and cognitive rules.

The paper offers three key insights. The first highlights how organizations can harness the open-ended design of weakly structured IS to unlock generative potential, such as integrating general-purpose modules like data analysis tools or leveraging digital trace data for innovation. This insight also underscores the challenges of implementing systems with 'unbounded possibilities,' which are 'emergent by design' and require implementation teams to continuously evaluate both the technology and organizational environment to identify problem-solution pairings that may only emerge through use. The second insight challenges the traditional linear approach to system implementation, arguing that it is unsuitable for weakly structured IS. Unlike highly structured systems that follow a fixed sequence, weakly structured IS require an ongoing, iterative process of adaptation and discovery. As organizations interact with these systems, evolving capabilities demand a flexible implementation strategy where humans and machines collaboratively develop new solutions. This underscores the need to shift from a linear mindset to a dynamic, continuous approach that aligns with the system's generative potential. The third insight highlights the need for governance practices that strike a balance between structured control and creative exploration, ensuring alignment between technology and organizational goals while fostering innovation. This study empirically illustrates how the dynamic development of uses and the corresponding creation of rules follow evolutionary patterns, reflecting how users gradually comprehend different system functions as their usage expands, stabilizes, and becomes institutionalized within the local context.

This paper contributes to the IS literature by offering a deeper understanding of weakly structured systems and their implementation dynamics. It demonstrates how balanced governance enables organizations to align diverse organizational goals with the system's open-ended technical capabilities.

4.2 Paper 2

Kandaurova, M., & Skog, D. A. (2024). *Initiating and expanding data network effects: A longitudinal case study of generativity in the evolution of an AI platform.* Proceedings of the 57th Hawaii International Conference on System Sciences (HICSS).

Paper 2 builds on recent theoretical claims proposing that data network effects (DNEs), a new type of network effect, are key to understanding how AI platforms grow and improve their algorithmic capabilities over time. These effects rely on the platform's ability to learn from data and enhance its offerings continuously. However, empirical evidence supporting these claims remains limited. Paper 2 sets out to empirically investigate and explain: *How do AI platforms grow and improve their algorithmic capabilities over time?*

Theoretically, this paper draws on Data Network Effects (Gregory, Henfridsson, Kaganer, E., & Kyriakou, 2022), and the concept of generativity as a sociotechnical system (Thomas & Tee, 2022). Empirically, it is based on a longitudinal case study design covering the development and evolution of a conversational low-code AI platform from 2010 to 2022.

Findings illustrate how the platform’s generative potential and its user community (i.e., the platform ecosystem) interact in a cyclical process that drives platform evolution. This process begins with new functions that enhance the platform’s generative capacity, allowing existing users to utilize platform resources in new ways and create innovative outcomes. These outcomes further expand the platform’s capabilities, benefiting the current user base and deepening their engagement. As these improvements demonstrate value, they attract new users, leading to a growing and more diverse user community. The resulting increase in data enables the platform to learn, adapt, and improve further, reinforcing the generative feedback loop and driving continuous system growth.

The paper makes three key contributions. First, it provides empirical validation of DNEs, a concept previously proposed theoretically but not tested in practice. It demonstrates how AI platforms evolve by initiating and expanding DNEs through generative feedback loops. These loops are triggered by platform enhancements that enable the creation of diverse data, which in turn improves AI capabilities. The study further refines our understanding of DNEs by highlighting the importance of how platforms access and integrate data to support continuous learning and improvement, as well as the conditions necessary for DNEs to emerge and grow. Second, the paper broadens the understanding of ecosystem actors' roles in the emergence of DNEs. It challenges the narrow focus on platform providers and app developers by showing that DNEs are also shaped by a broader range of participants, including clients and competitors. The study highlights the dynamic interactions among these actors, such as clients requesting new features and competitors introducing innovations, that drive generative feedback loops and contribute to platform evolution. Third, the paper highlights that AI platforms can enhance DNEs not only by learning from user data but also by integrating data from other sources, such as internal client systems or external web services enabled by third-party interfaces. This finding challenges the traditional focus on tightly governed resources (e.g., Ghazawneh & Henfridsson, 2013), and suggests that AI platforms can benefit from encouraging a broader scope and scale of ecosystem contributions. This paper contributes to IS literature, specifically digital platform literature, following recent calls to empirically examine DNEs to better understand how AI platforms evolve their algorithmic capabilities over time.

4.3 Paper 3

Kandaurova, M., Skog, D. A., & Bosch-Sijtsema, P. (2024). The Promise and Perils of Low-Code AI Platforms. *MIS Quarterly Executive*, *23*(3), 275-289.

As part of the MISQ Executive special issue, Paper 3 informs practitioners about the opportunities and challenges of low-code AI platforms, which combine user-friendly development environments with advanced AI capabilities to enable non-technical users to create smarter, automated applications that mimic human cognition. While low-code platforms are often praised for democratizing AI implementation, this paper takes a critical perspective, exploring: *What challenges exist in the implementation of low-code AI platforms and how can organizations overcome these challenges?*

Theoretically, the paper builds on Zittrain's (2008) concept of generative capacity. Empirically, it draws on a case study of the implementation of a low-code conversational AI platform in four multinational companies: EnerCo, AutoCo1, AutoCo2, and RetCo.

Findings reveal three key challenges rooted in false assumptions about the platform's usability, adaptability, and integrability. First, organizations assumed that low-code platforms would allow anyone to develop applications without coding or AI expertise, however, even non-technical users required a basic understanding of coding concepts. Second, while low-code platforms were expected to adapt easily to various business contexts, significant customization and process adjustments were often required. Finally, the assumption that these platforms would seamlessly integrate with existing back-end systems proved problematic, as misalignment with databases and systems necessitated redesign efforts.

The paper presents three key insights as actionable recommendations to address the identified challenges. The first insight addresses the misconception that low-code platforms are universally intuitive and easy to use for non-IT staff. It emphasizes the importance of collaboration between IT and business teams to unlock the full potential of these platforms through deliberate, iterative use and shared expertise. The second insight underscores the need to analyze, standardize, and reengineer business processes to ensure AI compatibility and successful automation, as low-code platforms cannot bypass the complexities of human-operated processes. The third insight stresses the need to go beyond the user-friendly front-end of low-code platforms and prebuilt connectors. It urges companies to thoroughly evaluate their data management and back-end system integration capabilities, as these are critical to the success of the platform and its applications.

This paper primarily contributes to practice by informing information systems practitioners and C-Suite managers about the challenges and pitfalls of adopting low-code AI platforms, particularly focusing on the false assumptions surrounding how low-code environments are perceived. The paper highlights how these assumptions can lead to unrealistic expectations about democratizing AI use and emphasizes the need for a more nuanced understanding of low-code platforms' limitations and requirements.

4.4 Paper 4

Mansoori, Y., Kandaurova, M., & Bumann, A. (working paper). *'Everyone' Can Be an Entrepreneur: The Rise of Low-Code/No-Code Entrepreneurship.*

Paper 4 explores and describes the impact of Low-Code/No-Code (LC/NC) tools on venture creation processes in digital entrepreneurship. LC/NC tools allow individuals with limited technical expertise to create products and services without extensive coding knowledge. These tools, which feature visual interfaces and pre-built components, lower barriers to entrepreneurship by enabling rapid venture development. The paper focuses on how LC/NC tools influence different stages of venture creation processes, including idea validation, minimum viable product (MVP) development, and market launch. One way to understand how these tools enable and constrain entrepreneurial practices is through technology affordances theory. Paper 4 aims to explore and describe: *What functional affordances do LC/NC platforms offer, and what opportunities and constraints do they present for different venture creation processes in digital entrepreneurship?*

Empirically, the paper draws on a scoping literature review and uses two fictitious case studies to demonstrate the impact of LC/NC tools on entrepreneurship. These case studies highlight the advantages of LC/NC tools in accelerating MVP development and market entry, while also revealing limitations in scalability and customization. The paper employs thematic analysis to synthesize literature, using technology affordance theory and the concept of generative capacity as a foundation for exploring how LC/NC tools influence digital entrepreneurship.

The findings identify five functional affordances of LC/NC tools: accessibility, integrability, adaptability, cooperability, and scalability. These affordances enable entrepreneurs to quickly validate ideas, develop MVPs, and adapt to market changes, but they also create tensions between speed and performance, standardization and creativity, and empowerment and dependency.

The paper offers three key insights. First, it shows how LC/NC tools democratize entrepreneurship by making venture creation accessible to non-technical individuals, while cautioning about the trade-off between speed and performance. Second, it highlights that although LC/NC tools are highly beneficial for early-stage ventures, they can pose challenges for scalability and customization as businesses grow. Third, it stresses the need to align LC/NC tools with long-term business goals, balancing the immediate advantages of rapid development with the future need for technical growth and flexibility as ventures evolve.

This paper contributes to the digital entrepreneurship literature by deepening our understanding of how LC/NC tools impact venture creation processes. It provides practical implications for entrepreneurs, investors, and entrepreneurship educators, highlighting the need for a balanced approach that leverages the strengths of LC/NC tools while mitigating their long-term limitations.

4.5 Synthesis of Papers

The papers discussed above collectively illustrate how large organizations pursue value creation through the implementation of a low-code AI platform (Papers 1 and 3) and how the platform's architecture influences this process (Papers 2 and 4). Together, they highlight the sociotechnical nature of the implementation process, where IT capabilities must align with the organizational environment. This alignment requires both technology and the organization to adapt and evolve before value creation can occur and manifests in three key adaptation processes, such as *Cognitive Understanding, Contextual Adaptation, and Infrastructure Compatibility Evaluation.* These adaptation processes form the foundation for aligning the platform’s capabilities with organizational needs to pursue value creation. These iterative and self-reinforcing processes enable organizations to bridge cognitive gaps, tailor the platform to specific contexts, and ensure seamless integration with existing infrastructures.

Regarding *Cognitive Understanding,* Papers 1 and 3 reveal a significant cognitive gap between technical and non-technical experts regarding the platform's low-code features and AI capabilities. Initially, both groups viewed the low-code environment as a gateway to accessible AI application development, however, non-technical experts encountered a steep learning curve. They also faced challenges understanding how to work with the platform’s AI capabilities, including identifying appropriate input data, interpreting outputs, and legitimizing the platform’s results. These challenges prompted organizations to engage in cognitive understanding processes to develop a shared and congruent understanding of the technology. In fact, Paper 1 illustrates that organizations achieving stronger implementation alignment between the platform’s capabilities and their organizational environment employed cognitive rules. These rules clarified the platform’s technical capabilities and limitations, shaping what was encouraged and acceptable while fostering a shared perspective on how the platform aligned with both current and future organizational goals. Similarly, Paper 3 demonstrates how the hype surrounding AI and low-code development heightened the need for cognitive understanding, as it led organizational actors to form misconceptions about the platform’s true capabilities. Additionally, senior management, influenced by this hype, often failed to critically assess the long-term requirements needed to implement and maintain the system effectively. The paper illustrates that taken-for-granted assumptions about the implemented low-code AI platform, without critically examining its practical implications and implementation requirements, created significant challenges, thus highlighting the importance of developing a holistic cognitive understanding of technology among a heterogeneous community of actors who work with it.

Regarding *Contextual Adaptation,* the findings reveal that while the platform was designed as a general-purpose system capable of facilitating human interactions across various domains and languages, it required substantial contextualization to meet the unique needs of organizations. Due to the low-code nature of the platform, with its prebuilt modules, linguistic capabilities, and interface libraries, enabling rapid creation of simple AI applications, organizations initially perceived it as a plug-and-play solution. However, expanding its knowledge base required training the platform on context-specific data, such as products, services, and business processes targeted for automation, that were often uncodified and embedded with tacit elements requiring standardization. As illustrated in Paper 3, this oversight emphasized the importance of first analyzing and standardizing business processes to align with the platform's requirements. Paper 1 further shows that successful adaptation required organizations to move away from treating the platform as a plug-and-play tool. Instead, they adopted technical rules that intentionally slowed the implementation process, allowing for the revision of business processes, iterative platform training, updates to algorithms and databases, and adaptation of the platform’s capabilities to meet the organizations’ contextual needs.

Finally, regarding *Infrastructure Compatibility Evaluation,* the findings reveal that the platform's implementation and value-creation potential depend on its continuous reconciliation with existing technical legacy systems. While the platform's architecture provides a library of prebuilt interfaces, such as APIs and SDKs, to connect with front-end and back-end systems and databases, organizations discovered that these systems were not as compatible as initially expected. Moreover, they often found that new interfaces needed to be built to deliver the required connectivity as new functions and use cases of the platform were explored. As illustrated in Paper 3, organizations had to identify diverse data sources, both global and regional, that the platform and its applications relied on for input. However, these data sources were often unavailable in the formats and structures required by the platform. This misalignment forced organizations to take a step back, conduct infrastructure compatibility assessments, and reconfigure their existing systems to meet the platform's requirements. This process highlighted a self-reinforcing dynamic: as organizations aligned their systems to ensure compatibility, they unlocked new capabilities and value-creation opportunities. For instance, as indicated in Paper 3, some case companies, after evaluating and restructuring their internal back-end systems and databases, revised their data management and protection strategies to ensure they were future-ready and suitable for external sharing. These improvements, in turn, revealed additional integration needs, prompting further evaluation and restructuring. This ongoing, cyclical effort enabled the platform to better integrate with legacy systems, supporting continuous evolution and value creation.

Together, these adaptation processes form a self-reinforcing loop, where improved cognitive understanding initiates the cycle by aligning the knowledge and perspectives of diverse actors regarding the platform, its AI capabilities, and low-code features. This enables more effective contextual adaptation of the platform, leading to tailored applications and use cases. These adaptations necessitate infrastructure compatibility assessments, which ensure systems are aligned, integrated, and fit the platform's requirements. Each cycle generates new insights, opportunities, and use cases that feed back into cognitive understanding, strengthening collective knowledge and inspiring further iterations. This cyclical effort, as illustrated in Paper 1, resembles *"metahuman systems",* where humans and machines adapt to collaboratively learn to develop new systemic capabilities. Unlike traditional, sequential implementation processes, this approach is ongoing and iterative.

Additionally, all four papers demonstrate that the platform plays two pivotal roles. These are depicted in blue dotted lines in Figure 1. The first role is that the platform necessitates organizations to rethink their approaches and embrace broader organizational change. For example, unlike traditional implementations, where IT departments were solely responsible for developing and deploying applications, the platform's low-code development environment allows a diverse group of actors, including non-technical experts, to actively participate in the implementation process. This inclusion not only democratizes and speeds up AI application development but also accelerates it by leveraging a wider range of perspectives and expertise. Moreover, the platform's need for contextual embedding to learn and improve over time shifts responsibility from IT to business experts. Those seeking to automate their business processes through AI must now take greater ownership of ensuring the platform's ongoing learning, training, and relevance to their specific operational needs. In parallel, as evident in Papers 1 and 3, the role and responsibilities of IT experts evolve significantly. They must oversee an increasing number of AI applications across various organizational domains while ensuring a cohesive understanding of the platform among the diverse actors involved in its implementation. The platform's open-ended nature often leads to varied interpretations of its functions and capabilities, making it essential for IT experts to unify these perspectives. This expanded role requires not only technical expertise but also a deep understanding of the business processes the platform supports. By bridging the gap between technical and business perspectives, IT experts play a crucial role in aligning the platform with organizational goals and ensuring its effective implementation.

The second role is that the platform enables organizations to leverage end-user data in two key ways: a) to support the continuous evolution of the platform and its applications by enhancing their capabilities and functions, and b) to improve business operations while shaping strategic decisions and guiding future directions. For instance, Paper 2 highlights how the platform utilizes diverse data sources, including end-user data, to enhance its AI capabilities and low-code functionality. Similarly, Paper 1 demonstrates how the platform, by learning from end-user data, helps organizations uncover new use cases and develop derivative innovations, such as introducing new products or services, while informing decision-making processes.

When taken together, the findings and key insights from the appended papers discussed above contribute to the development of a conceptual process model (Figure 1) that can help illustrate, and thus better explain, the dynamics in pursuit of value creation by large organizations when they implement a low-code AI platform. I discuss this process model in detail in the following chapter.

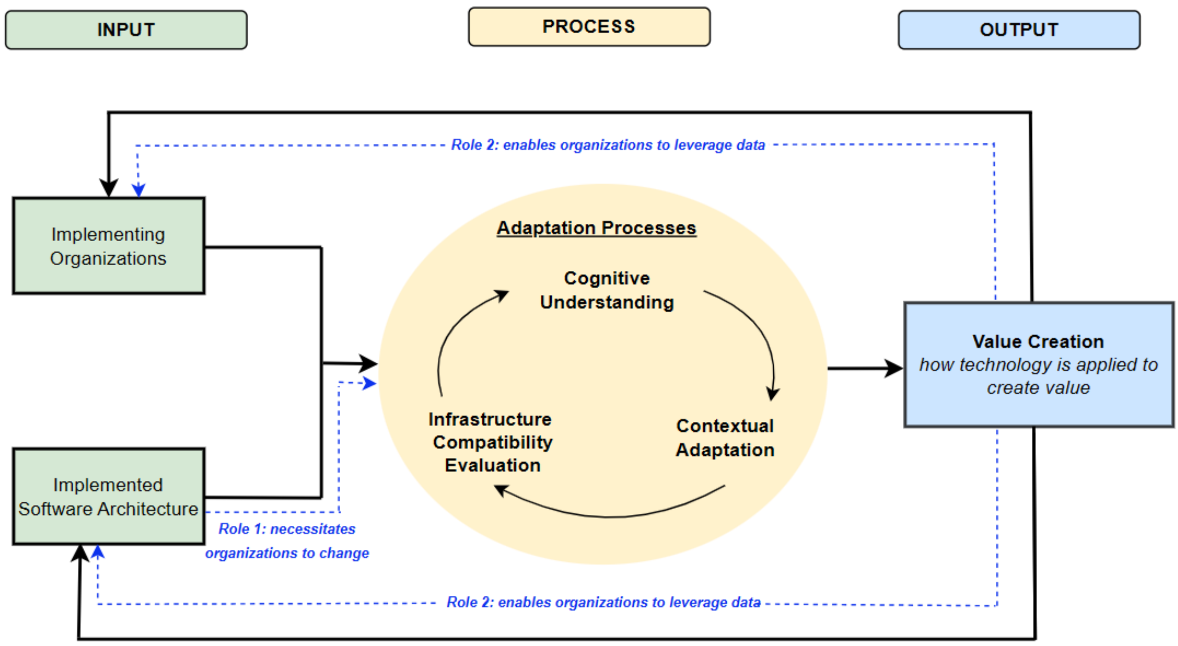

Figure 1. *A conceptual process model of low-code AI platform implementation in pursuit of value creation in large organizations*

5. Discussion

The following chapter sections summarize the key findings and conclusions in relation to the two research questions addressed in this thesis. For convenience, the research questions are listed below:

> RQ1: How do large organizations pursue value creation when implementing low-code AI platforms?
>
> RQ2: How does the platform influence this process?

This chapter concludes with a discussion of the theoretical and practical implications of the work presented in this thesis, along with its scope limitations and suggestions for future research.

5.1 Understanding Processes Leading to Value Creation Through Low-Code AI

Findings from Papers 1 and 3 provided the basis for answering the first research question. Organizations implement new technologies to generate some form of value. A significant body of research has explored the link between technology implementation and the value it creates (Kohli & Grover, 2008). In recent years, the adoption of AI-based systems across various organizational contexts has surged, with the goal of enhancing operations and securing a competitive edge (Dwivedi & Wang, 2022; Mikalef et al., 2021). AI is often regarded as the next frontier for competition and productivity (Dwivedi et al., 2021) or as a transformative force that will radically change how businesses operate (Ågerfalk, 2020). However, despite these claims, empirical research on the value of AI remains in its early stages, and there is still a limited understanding of the specific processes organizations must undertake during implementation to realize the value creation associated with a newly implemented AI system.

Research indicates that the primary path to value creation in the implementation of a new technology lies in the creation of *"structures and other complementary assets (process and human capital changes) that can leverage the technology"* (Baiyere, Grover, Lyytinen, Gupta, & Woerner, 2020, p. 472). Insights from Papers 1 and 3 suggest that organizations that implemented a studied low-code AI platform in pursuit of value creation engaged in three adaptation processes, understood as essential, high-level activities critical for aligning new technology with the organizational environment. These processes are *Cognitive Understanding, Contextual Adaptation, and Infrastructure Compatibility Evaluation,* with *Cognitive Understanding* emerging as the first critical step. Below, I elaborate on each of these processes and their underlying activities, connecting them to previous literature and empirical findings.

Cognitive Understanding is the process by which organizations develop a comprehensive and shared understanding of a new technology's capabilities, including its opportunities, limitations, and dependencies**.** This involves exploring and aligning different cognitive frames held by technical and non-technical experts, with the aim of establishing a unified technological frame among implementation team members and defining shared implementation boundaries for a use case. In this process, the social actors involved with the technology adapt and align their diverse perspectives, mental models, and understanding of the platform's capabilities, limitations, and strategic potential. This shared understanding enables diverse team members to engage in more coherent, purpose-driven technology implementation.

The importance of a unified cognitive understanding in technology implementation is well-supported in IS literature. Previous studies have highlighted technological frames, i.e., a set of assumptions used by social actors to understand and apply technology within their organization, as key to this process (Gash & Orlikowski, 1991; Ivarsson, 2022; Mishra & Agarwal, 2010). Ivarsson (2022) underscores the importance of understanding the *"framing processes"* in complex and emerging digital technologies, including artificial intelligence, as these technologies carry profound organizational implications.

Building on framing theory and the technological frame of reference (Orlikowski & Gash, 1991, 1994), cognitive understanding can be viewed as a construction of meaning around a new technology, such as a low-code AI platform. This process is inherently dynamic, social, and ongoing, where actors actively *"(re)think, (re)interpret, or (re)shape meanings of technologies within a specific organizational context"* (Ivarsson, 2022, p. 6373). IS literature has shown that these processes of meaning-making are essential not only for understanding the technology's implementation and use but also for its broader organizational impact (Orlikowski & Gash, 1994). Essén and Värlander's (2019) concept of recursive mechanisms provides additional insight into this meaning-making process. These mechanisms, consisting of *material reconstruction, emergent use, and discursive reconstruction*, highlight how social actors interact with technology to iteratively adapt and reshape both the technology and its surrounding practices. Through material reconstruction, actors modify and reconfigure the technology's features to align with organizational needs, while emergent use involves hands-on, experimental engagement to uncover novel applications. Discursive reconstruction helps articulate and share evolving interpretations of technology's role, fostering shared understanding across diverse stakeholders. Contemporary organizations must continually engage in such meaning-making processes to fully grasp and adapt the features, capabilities, and potential of generative technologies (Ivarsson, 2022), as understanding them is essential for guiding actions toward realizing value creation (Davidson, 2006).

The need for such cognitive understanding is particularly pronounced with flexible, generative technologies, which differ significantly from non-generative systems like ERP that have fixed, well-defined functions and outcomes and thus offer formalized rules for organizational coordination (Ajer, Hustad, & Vassilakopoulou, 2021; Berente, Lyytinen, Yoo, & Maurer, 2019). Generative technologies, with fluid architectural boundaries and open-ended functionality, are more akin to open canvases, allowing organizations to shape them according to their unique goals and needs. This open-ended nature makes it challenging for organizational members to fully comprehend the technology's capabilities and potential applications. Literature suggests that these *"emergent by design"* technologies (Nambisan et al., 2017) require implementation teams to continuously assess both the technology and the organizational environment to identify suitable problem-solution pairings (von Hippel & von Krogh, 2016), highlighting the need for ongoing cognitive understanding processes.

Empirical findings from Papers 1 and 3 highlight that the cognitive understanding process is a crucial first step in implementing low-code AI platforms. Unlike traditional implementation and application development processes, which primarily involve IT experts, the low-code development environment allows a more diverse group of actors to participate in the platform's implementation and the development of AI-based applications. While such heterogeneity fosters the emergence of a generative community, or *"generative collectives"* as described by van Osch and Avital (2010), that can actualize the generative potential of the platform's architecture (Avital & Te'eni, 2009; Faraj et al., 2011), it also introduces challenges. Literature shows that these generative communities have different experiences and assumptions, and thus can perceive a newly implemented technology differently (Arazy et al., 2020; Dokko et al., 2014; Nambisan, 2017). The incongruent views of new technology can hinder its successful implementation and lead to difficulties regarding the technological and the organizational changes that take place during the implementation process (Orlikowski & Gash, 1994; Young, Mathiassen, & Davidson, 2016). To overcome these challenges and actualize the generative potential of the platform's architecture, the diverse groups must align their perspectives and understanding of the platform's capabilities, implementation approach, and value potential. This alignment establishes a strong foundation for successful implementation and value creation.

As illustrated in Papers 1 and 3, organizations that successfully bridged this cognitive gap fostered diverse implementation teams and encouraged dynamic, ongoing cross-functional collaboration, where technical and non-technical experts could openly share their assumptions, challenges, and misunderstandings about the low-code AI platform. These activities proved to be effective, as through the ongoing discourse between community members on the interpretation and use of the platform's generative architecture (Arazy et al., 2020; Hoever et al., 2018; Ovrelid & Bygstad, 2019), they were able to narrow down the use cases and set collective implementation goals. Through targeted training programs, workshops, and onboarding sessions, these collaborative efforts helped heterogeneous users develop a cohesive understanding of the platform's potential, limitations, and growth requirements. Moreover, these cross-functional activities enabled organizations to better identify and understand their own business processes that could benefit from automation through the low-code AI platform. By working together in this way, business leaders, coding specialists, and AI experts not only gained a deeper understanding of the platform's components but also developed richer insights into their organization's business dynamics, supporting more effective and aligned implementation. Research suggests that heterogeneous groups engaged in cognitive understanding processes around generative technology are more likely to unlock its generative potential and thus lead to new value paths (Avital & Te'eni, 2009; Faraj et al., 2011). Their diversity in skills, expertise (Boland, Lyytinen, & Yoo, 2007), and varied perspectives (Svahn et al., 2017) enable them to collectively expand their knowledge of the technology. This process of testing assumptions and challenging the status quo makes these groups particularly effective in exploring and realizing the technology's potential.

Another critical activity organizations engaged in to bridge the cognitive gap was encouraging their heterogeneous implementation teams to explore and experiment with the system's opportunities and limitations. Paper 1 illustrates that differing interpretations of what constitutes a valuable outcome emerged among organizations. Many viewed the low-code AI platform primarily as a tool to augment operational efficiency, while others saw it as a means to tap into the platform's generative and long-term potential. This contrast in perspective led to creative applications and the exploration of secondary value opportunities, particularly for organizations willing to go beyond immediate efficiency gains. Paper 1 shows that organizations that arrived at a cognitive understanding of the platform's flexible design as an open field encouraged their implementation teams to prototype diverse applications, leveraging low-code capabilities to support iterative learning and adaptation. This approach not only broadened the teams' understanding of the platform's generative potential but also fostered organizational learning and the alignment of long-term strategic objectives with the technology's evolving uses. Research suggests that balancing exploration and exploitation is essential for organizational learning and long-term success, as an overemphasis on exploitation can lead to a lack of innovation and adaptability (March, 1991). For organizations implementing flexible, generative technology like a low-code AI platform, engaging in exploratory processes is key to discovering the full range of its capabilities and potential applications (Avital & Te'Eni, 2009).

Contextual Adaptation is the process by which organizations customize context-agnostic technology to align with the unique requirements and nuances of the environments in which it is implemented. Research indicates that digital technologies, particularly those characterized by generativity, are often designed with general-purpose functionality, making them inherently agnostic to specific industries and products (Henfridsson et al., 2018; Yoo et al., 2010, 2012). Their open-ended design makes them inherently interoperable (Yoo et al., 2012) and this interoperability enables scaling and creation of new complementary value paths across different contexts (Lehmann & Recker, 2021). For instance, the studied low-code AI platform can quickly scale its applications through frequent recontextualization and adaptation of its digital core technology (Huang, Henfridsson, Liu, & Newell, 2017) across multiple languages and contexts due to its prebuilt modules and linguistic capabilities that enable it to initiate and sustain human interactions, such as providing customer service support. However, because these technologies lack specialized knowledge, terminology, and workflows unique to individual organizations, they require contextualization and the localization of standards and adjustments to become practically useful in specific settings (Tilson, Lyytinen, & Sørensen, 2010). As Lehmann et al. (2022; p. 1455) emphasize, contextualizing such technologies, by *"addressing the here-and-now environment in terms of factors such as customer expectations, legacy technology, regulations, and market expectations",* is essential for unlocking their value creation. Through contextual adaptation, organizations can align technology with their organizational needs, maximizing its relevance and effectiveness in achieving desired outcomes.

As demonstrated in Papers 1 and 3, the studied conversational low-code AI platform was designed to facilitate communication by mimicking human interaction. Its low-code features, combined with prebuilt algorithms, interfaces, and linguistic capabilities, led organizations to believe it could be easily tailored to meet the specific requirements of any business domain. The platform's ability to quickly initiate and sustain human interactions across multiple languages and domains, due to prebuilt components and modules, reinforced the perception of it as a plug-and-play solution, requiring minimal effort for deployment and operation. Many organizations reported that they expected the system to become a domain *"guru"* that could quickly extend its knowledge base due to its AI capability to learn from data. However, organizations soon realized that while the platform could indeed handle general inquiries and interactions across multiple domains and languages, it lacked familiarity with the unique nuances of their specific organizational contexts. This included gaps in understanding the organization's products, processes, and services. In essence, the platform was initially context-agnostic and required significant contextualization to align with the organization's specific needs. Without this adaptation, such as training the system on context-specific data, documents, and workflows, the platform could not deliver its full potential. Paper 2 underscores that the quality and relevance of training data, rather than quantity, are critical for effective contextualization.

Generative technologies offer flexibility and adaptability across diverse contexts, but their broad applicability places significant responsibility on organizations to iteratively adapt these systems to meet their unique, context-specific requirements. Such contextualization can be highly challenging, especially in dynamic AI applications such as chatbots or voicebots, as they need to be trained on context-specific data to deliver flawless and relevant end-user experience (Elshan, Ebel, Söllner, & Leimeister, 2023). These challenges are illustrated in Paper 3 to a certain extent. Paper 3 demonstrates that, contrary to the common expectation that such systems could be easily adapted to organizational contexts and immediately generate AI applications with expert-level support, organizations encountered several limitations. They quickly realized that the system required substantial time and effort to be trained on a relevant knowledge base. In identifying what constituted a *"relevant"* knowledge base, organizations discovered the inherent complexity and variability of their human-operated processes. These processes often held critical contextual information essential for effective system training but were challenging to capture due to their tacit nature.

Bridging this gap necessitated an iterative, contextual adaptation process. As highlighted in Paper 3, the adaptation process involves several steps. First, organizations must assess and codify their existing business processes, identifying the specific workflows, terminologies, and contextual parameters that define their operational needs. These elements then need to be translated into technical configurations within the system, effectively adapting the technology to reflect organizational nuances. Subsequently, the adaptation process requires training the system to respond accurately within the organization's specific domain, embedding business logic and domain-specific tacit knowledge that the technology would otherwise lack. Eventually, the iterative adaptation process allows organizations to gradually expand the system's knowledge base and better understand the complexities associated with AI systems supporting diverse business operations. Notably, organizations faced challenges in adapting the platform to handle a broad range of customer inquiries, especially in B2C (i.e., business-to-consumer) rather than B2B (i.e., business-to-business) contexts, where queries are highly varied and dynamic.

Infrastructure Compatibility Evaluation is the process by which organizations assess and, if needed, reconfigure their existing infrastructures, such as legacy systems, databases, and communication networks (e.g., APIs) to ensure alignment with the requirements of the implemented technology. This process involves identifying and addressing compatibility issues that may hinder the flow of data and functionality between the organization's established systems and the new technology. By assessing infrastructure compatibility, organizations can determine the necessary adjustments, integrations, or upgrades required for seamless data exchange and the optimal performance of the implemented low-code AI platform, thereby ensuring the foundational systems can effectively support its AI capabilities.

Research underscores the importance of infrastructure compatibility evaluation as a critical step in achieving value from new technology implementations (Lehmann, Recker, Yoo, & Rosenkranz, 2022; Tarafdar & Gordon, 2007; Tilson et al., 2010; Weber, Engert, Schaffer, Weking, & Krcmar, 2022). For instance, Lehmann et al. (2022) suggest that while digital technologies possess generative potential, enabling rapid scaling and adaptability, they still need to be continuously aligned with existing technical infrastructures and the organizational context to unlock this value fully.

Existing infrastructures, such as legacy systems and databases, often create challenges for compatibility with new, generative technologies. Typically designed as internal, closed systems for specific, predefined purposes, such as managing payroll, inventory, or customer records, legacy infrastructures often lack the flexibility needed to support evolving applications and enable connections across organizational boundaries. Achieving seamless interoperability and data exchange between the low-code AI platform and these existing infrastructures requires a thorough infrastructure compatibility evaluation and reconfiguration.

For infrastructure compatibility practices, as shown in Papers 1 and 3, organizations engage in several key activities. First, they identify and evaluate specific systems, both regional and global, on which the platform and its applications rely on for input. Next, they determine the necessary data sources that the platform and applications need access to. Finally, organizations ensure that data structures and formats align with the platform's requirements, enabling the AI applications to access essential input and generate human-like output independently, without the need for human interpretation or adjustment.

While current literature emphasizes that infrastructure incompatibility, particularly between legacy systems and new technologies, is a common challenge in large organizations (Ghawe & Chan, 2022), insights from Papers 1, 2 and 3 reveal that this challenge is amplified by two factors. First, AI-based systems, such as the AI applications built on the studied low-code AI platform, are dynamic and rely heavily on continuous integration with foundational systems and databases for input. These integrations must provide real-time, live, API-connected data to support the AI applications effectively. Second, large organizations typically manage a complex array of regional and global systems and databases that must reflect constant updates, such as changes in customer preferences, new or retired products and services, and revised procedures and policies. This need for continuous updates, delivered in real-time through API connectivity, compounds the challenge of maintaining compatibility between legacy infrastructures and evolving AI technologies. Additionally, previous IS research has highlighted the importance of end-user data for the AI platform learning and improvement (Gregory et al., 2021). Paper 2 demonstrates that the AI platform is likely to enhance its algorithmic capabilities further when end-user data is complemented with data from internal systems, databases, and external web services covering a wide range of business contexts. These insights underscore the critical need for an *Infrastructure Compatibility Evaluation* process, enabling organizations to ensure seamless integration between legacy systems and dynamic AI technologies, thereby supporting real-time data exchange and adaptability in an ever-evolving market landscape.

These three adaptation processes, employed by organizations during the implementation of a low-code AI platform and essential for pursuing value creation, provide sufficient reasoning, supported by current literature and empirical insights, to address RQ1.

5.2 Understanding the Platform's Role in the Pursuit of Value Creation

Papers 2 and 4 provide key insights to address RQ2, with additional contributions from Papers 1 and 3 that further enrich the explanation. Based on my empirical observations of the appended papers, I propose that the platform plays two pivotal roles. First, the platform necessitates organizations to rethink their approaches, adopt greater flexibility in relation to the platform's implementation and use, and embrace broader organizational change.

Second, it enables organizations to leverage data through two distinct feedback loops: (1) a loop that continuously enhances the platform itself, known in literature as data network effects (DNEs) (Gregory et al., 2021), and (2) a loop that generates insights for improving business operations and strategy, a process referred to in literature as data-enabled learning (Hagiu & Wright, 2023).

Role 1: Platform as a Driver of Organizational Change

The generative architecture of a low-code AI platform serves as a dynamic force driving organizational transformation by actively engaging with the social components of the adopting organization, i.e., its structures, rules, practices, and the social actors involved in the implementation process. With its open-ended design and delayed binding of form and function (Yoo et al., 2010), the platform compels organizations to reimagine their practices, introducing flexibility and adaptability as essential components of their operations. The platform's architecture does not merely reflect organizational needs but actively projects its flexibility onto the organization, forcing it to rethink its routines and structures to harness the platform's transformative potential. When confronted with a system offering *"seemingly unbound possibilities for recombination, rapid scaling, and continuous innovation"* (Lehmann et al., 2022), organizations must navigate an open-ended landscape of value creation (Henfridsson et al., 2018). This wide array of possibilities acts as a catalyst for organizational change, compelling user communities to adopt heterogeneous, discursive, and flexible approaches (Thomas & Tee, 2022). By demanding adaptation at both strategic and operational levels, the platform transforms its role from a passive tool into an active agent, shaping the organization's path to innovation and growth (Essén & Värlander, 2019).

As illustrated in Paper 4, this active influence is further evident in how the platform's functional affordances are interpreted and activated by user communities (Stendal et al., 2016). For example, *accessibility*, i.e., a core functional affordance of a low-code platform, signals user-friendliness with visual, drag-and-drop interfaces (Rai et al., 2019) and conceptual models that facilitate idea development without extensive coding (Carroll & Maher, 2023; Heuer, Kurtz, & Böhmann, 2022). However, as discussed in Papers 1, 3, and 4, these affordances represent *"dormant technological capabilities"* that require activation through sociotechnical interactions. These interactions depend on foundational organizational processes and activities, essential for realizing the platform's potential. The affordance theory (Stendal, Thapa, & Lanamaki, 2016) posits that organizations' perceptions of new technology shape their response and implementation outcomes. When technology is perceived as a constraint, organizations might attempt to modify the technology to fit their established routines and practices. However, if technology is perceived as an opportunity, organizations tend to look inward, and adapt their norms, practices, and strategic directions to leverage its flexibility. Empirical observations show a similar pattern: organizations resistant to flexibility struggled to create value, while those that recognized the platform's generative potential adapted their practices and unlocked the platform's full value.

Role 2: Platform as an Enabler for Leveraging Data

The platform's second role is to enable organizations to leverage data accessed through the platform, facilitating two distinct feedback loops. The first loop centers on continuous improvements to the platform itself, enhancing its value to users over time as more users interact with it. This feedback loop, driven by cumulative user interactions, captures new phrases, inquiries, and intents, allowing the platform to adjust its response algorithms and expand its knowledge base to benefit all users. These adjustments enhance the platform's real-time responsiveness and collective intelligence, making it more useful and adaptable. For instance, chatbots powered by the platform become progressively smarter at responding, troubleshooting, and predicting issues based on collective user behavior, thereby strengthening the platform's internal functions and AI capabilities for all users. This feedback loop, known as Data Network Effects (DNEs) (Gregory et al., 2021; Paper 2), highlights how AI-based platforms expand their algorithmic capabilities over time, continuously improving for everyone based on accumulated interactions.

The second feedback loop impacts organizational capabilities and strategy beyond the platform itself. As illustrated in Papers 1 and 3, this loop allows organizations to gather actionable insights from user interactions on the platform, informing strategic decisions and operational improvements. For example, data accessed through chatbots provides insights into trends in customer preferences, recurring issues, or emerging needs. These insights empower organizations to develop new products, services, or strategic initiatives based on actual customer data. Paper 1 shows how organizations used this feedback loop to explore derivative innovations based on user data. This second feedback loop aligns with data-enabled learning, which refers to self-reinforcing processes where companies enhance their products and strategies by leveraging customer insights (Hagiu & Wright, 2023).

5.3 A Conceptual Process Model of Low-Code AI Implementation

The adaptation processes and two key roles of the platform discussed above form the foundation for the conceptual model of low-code AI implementation in pursuit of value creation in large organizations (Figure 2). Below I elaborate on the different components of the model and explain how they were informed by both the literature and empirical insights.

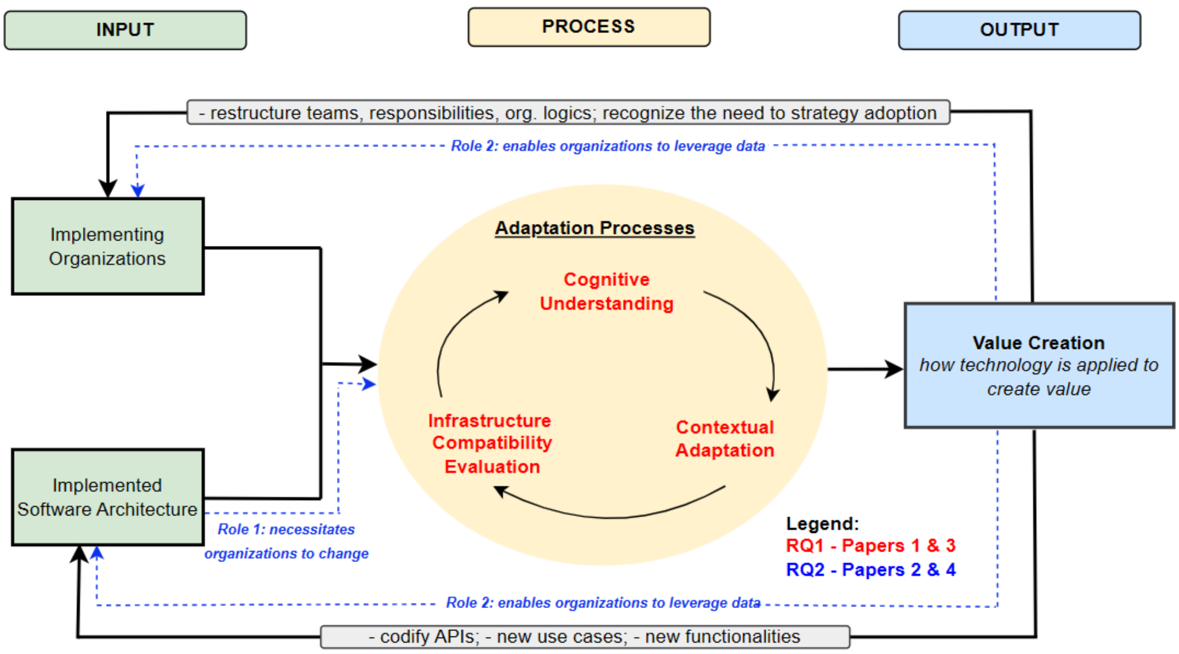

Figure 2. *A conceptual process model of low-code AI platform implementation in pursuit of value creation in large organizations (modified to illustrate relevance to research questions)*

This model can be viewed through the lens of sociotechnical systems theory, where (1) social (e.g., the organization, its governance practices, and human actors) and technical elements (e.g., the software architecture, platform capabilities) interact in a dynamic, iterative process. The interaction between these two elements is shaped by (2) adaptation processes organizations go through during the implementation, such as Cognitive Understanding, Contextual Adaptation, and Infrastructure Compatibility Evaluation, which are essential for realizing value from the platform. Ultimately, this leads to (3) outcomes in the form of new value paths, (4) that enable the establishment of feedback loops to ensure continuous adaptation and value creation in relation to the platform and its evolution, and in relation to the organization and its evolution over time.

Implementation of Low-Code AI as a Sociotechnical Process

Drawing broadly from the literature on IS implementation, the key objective of the implementation process is to align new IT capabilities with the organizational environment (Arvidsson et al., 2014; Chan, Huff, & Copeland, 1997; Leonard, 1988). This thesis, informed by both literature and empirical insights, characterizes the implementation of a low-code AI platform in pursuit of value creation as a sociotechnical process. This approach emphasizes the need for alignment between the platform's technical capabilities and the organization's social elements to fully realize the value from its implementation. This view is also in line with how systems conducive to generativity have been lately discussed as sociotechnical systems that comprise generative inputs (e.g., the implemented platform with its flexible and open-ended nature, and the implementing organizations with their established structures and ways of working), processes, and outcomes (Thomas & Tee, 2022).

This perspective is particularly crucial when dealing with weakly structured systems (WSS), which are characterized by affordance ambiguity, user-driven emergence, and functional equivocality. Rather than following a sequential process of 'unfreeze-implement-freeze'

(Berente et al., 2016; Cooper and Zmud, 1990) common to highly structured systems (HSS) with a predefined functionality, which assumes a linear, structured approach to implementation, weakly structured IS, such as a low-code AI platform, resemble *"metahuman systems"* (Lyytinen et al., 2020) in which humans and machines need to engage in joint adaptation processes to create new and original systemic capabilities, allowing for dynamic and adaptive value creation throughout the implementation process.

In line with Leonard's (1988) seminal work, this thesis views the implementation of a low-code AI platform not simply as a matter of adjusting the technology to fit within the organization or considering how the technology transforms the organization. Rather, it is understood as a sociotechnical process of mutual learning and adaptation, where both organization and technology evolve together to drive value creation. As demonstrated in the appended papers, the flexibility and generative potential of low-code AI platforms require a continuous process of learning and alignment between the platform's capabilities and the organization's goals. The four papers built on this sociotechnical perspective empirically illustrate that the locus of generativity lies in the interactions between the technology's generative capacity and the user community that engages with it and gets amplified by the established feedback loops once the technology is up and running.

Adaptation Processes

Current literature emphasizes the importance of balanced governance practices (Svahn et al., 2017; Thomas & Tee, 2022), specifically its mediating role in the alignment of technical and social elements when organizations deal with generative systems. This type of governance is deemed important to afford exploration of digital options (Svahn et al., 2017). It allows organizations to maintain control to ensure the stability of generative systems while allowing for openness. This balance enables implementing organizations to explore the platform's open-ended potential without constraining their creativity in using the system to achieve maximum value (Svahn et al., 2017; Thomas & Tee, 2022). While the balanced governance approach suggests how organizations should handle implementation, it does not provide the details of the specific processes involved in pursuing value creation with generative systems. This thesis and the process model above identify adaptation processes that organizations engage in while pursuing value creation during the implementation of a low-code AI platform.

Value Creation as an Outcome

Current literature on value creation through AI systems highlights their potential to improve efficiency, productivity, and overall business performance, emphasizing the augmentation of operational capabilities within organizations (Benbya et al., 2021). However, empirical research on AI's value generation is still in its early stages, with a limited understanding of the specific processes, practices, and mechanisms that enable organizations to realize business value from AI (Duan, Edwards, & Dwivedi, 2019; Mikalef, Conboy, & Krogstie, 2021).

In line with current literature, this thesis illustrates that value, in the context of technology adoption for digital transformation, can only be extracted through *"a conscious and deliberate entanglement of physical, technical, and social systems"* (Saarikko et al., 2020, p. 837). However, it offers a nuance - implementing low-code AI platforms brings two types of value: short-term and long-term. Short-term value emerges from automating business processes, delivering immediate efficiency gains. However, this value largely supports digitization and

IT-enabled innovation (Baiyere et al., 2020), with the initial organizational focus often too narrowly centered on short-term returns. Many organizations, as illustrated in the appended papers, initially relied on the promise of low-code to democratize AI development, viewing it primarily as a tool for process automation and workforce reduction, a way to digitize existing processes quickly.

Long-term value, however, lies in the platform's potential to drive broader digitalization, enabling organizations to transform how they work and conduct business (Saarikko et al., 2020). The empirical findings suggest that the true value of these platforms unfolds over time, as they foster continuous improvement and innovation. Through ongoing data collection, organizations can expand the platform's capabilities and applications, gathering real-time customer insights that become a sustained source of enhancing products and services. This long-term value, however, depends on active customer engagement with the platform, as continuous communication and feedback loops are essential for realizing this potential.

Feedback Loops - Continuous adaptation and ongoing value creation

Feedback loops enabled by the platform are essential pathways, or *"blood vessels"* that amplify and continuously drive value creation for organizations. This process model suggests that the creation of new value, e.g., automating a business process, is not a final objective, but rather a dynamic and iterative outcome within a broader cycle of organizational learning, adaptation, and improvement. The model highlights the platform's feedback loops as mechanisms for continuous improvement and adaptation, enabling organizations to unlock and expand the platform's value-creation potential over time. Specifically, organizations can generate ongoing value in two ways: (1) upgrading the platform and its applications over time through data network effects, thereby increasing the platform's value over time, and (2) leveraging end-user data to engage in data-enabled learning, which enhances business operations, drives innovation, and sustains a competitive advantage.

5.4 Implications for Research & Practice

The findings of this thesis have implications for both theory and practice.

Theoretical Implications

This thesis contributes to the Information Systems (IS) literature on implementation (Berente et al., 2016; Cooper & Zmud, 1990) by advancing the understanding of the implementation processes of low-code AI platforms characterized by generativity. While traditional IS literature often conceptualizes implementation as aligning IT systems with business environments, a relatively straightforward process for technologies with predefined functions, low-code AI platforms present unique challenges. Their generativity and malleability make alignment more complex due to their fluid and open-ended nature. This study enriches theory by exploring the adaptation processes organizations use to align these systems with their organizational contexts, challenging simplistic assumptions about their ease of implementation. Scholars such as Bailey and Barley (2020) have emphasized the need for a continuous, unified approach to implementing dynamic systems like AI platforms, which evolve through ongoing input, learning, and adaptation. Traditional implementation models, which treat design, deployment, and use as distinct linear phases, fail to capture the iterative and interconnected nature of these systems. By reconceptualizing implementation as a dynamic sociotechnical process, this thesis highlights how generative systems simultaneously offer affordances and constraints (Majchrzak & Markus, 2012) shaped by the organizational contexts they are embedded in. These factors lead to varied and often unanticipated outcomes, as Bailey and Barley (2020) note: *"the same technology can lead to very different and often unanticipated outcomes in different workplaces"* (p. 5). Implementation is thus an ongoing interaction between technology and the organizational environment it is implemented in, unfolding across diverse value paths that evolve over time. This perspective underscores the need for continuous adaptation to ensure these systems remain relevant and beneficial.

This thesis also extends our understanding of low-code AI platforms, which are increasingly recognized as *"next-generation"* digital platforms with the potential to democratize AI development. While low-code AI platforms are often perceived as straightforward due to their user-friendly features like drag-and-drop interfaces and prebuilt components, this view is misleading. This thesis emphasizes that their implementation is far from straightforward. Unlike fixed-function technologies with predefined outcomes, low-code AI platforms exhibit a fluid and open-ended nature, requiring organizations to navigate complex sociotechnical dynamics. This research highlights the continuous alignment required between the platforms' generative architecture and the organizational environments they are embedded in, demonstrating that successful implementation is a dynamic, iterative process. By addressing gaps in existing literature, this thesis sheds light on the processes that enable value creation with low-code AI platforms, including the cognitive, contextual, and infrastructural adaptations necessary to align these systems with organizational goals. It also illustrates how these platforms push organizations to rethink their workflows, adopt more flexible ways of working, and engage in continuous learning and adaptation. In doing so, this research not only advances our theoretical understanding of low-code AI platforms as generative systems but also offers practical insights for leveraging their full potential to drive innovation and long-term organizational transformation.

This thesis also contributes to the literature on generativity and generative systems by challenging the deterministic and technology-centric view of generativity. While existing IS literature often assumes that the layered modular architecture of digital platforms inherently drives generativity, this perspective tends to emphasize technology's structural attributes, adopting a deterministic and overly simplistic view. Such frameworks suggest that the architecture alone enables continuous recombination of modules, fostering innovation and value creation. However, this approach overlooks the critical role of organizational context, human agency, and sociotechnical processes in realizing the generative potential of these platforms. This thesis challenges the assumption that generativity is an inherent quality of the technology itself. By investigating the adaptation processes that organizations employ during the implementation of low-code AI platforms, it provides a more nuanced understanding of how generativity is co-created through the interplay between platform affordances and organizational practices. These adaptation processes: *cognitive understanding, contextual adaptation, and infrastructure compatibility evaluation*, highlight the active role that implementers, users, and organizational structures play in unlocking the generative capabilities of low-code AI platforms. For example, the study demonstrates how organizations must align diverse perspectives within implementation teams, tailor the platform's open-ended capabilities to meet specific business needs, and reconfigure legacy systems to support seamless integration. These efforts show that generativity is not an automatic outcome of the platform's modular architecture but rather emerges from a dynamic, iterative process of sociotechnical adaptation. By shifting the focus from a purely technology-driven view to a sociotechnical perspective, this research advances our understanding of generative systems like low-code AI platforms. It emphasizes that their potential for unanticipated innovation and value creation depends not just on architectural design but on how organizations actively engage with, adapt, shape and are shaped by these platforms. This perspective highlights the need for continuous alignment and iteration, demonstrating that generativity is a collaborative outcome of technology, organizational actors, and their environments.

Finally, this thesis contributes to theory by introducing a process model that provides a comprehensive understanding of how large organizations pursue value creation when implementing low-code AI platforms. By examining the nuanced dynamics involved, the model reveals what it truly takes to *"democratize AI"* (Sundberg & Holmström, 2023) and how such implementations lead to profound and qualitative changes within organizations. The process model challenges the oversimplified notion that low-code AI platforms inherently democratize AI by making it accessible to non-technical users through intuitive interfaces and pre-built components. While these features reduce entry barriers, the model illustrates that democratization requires more than ease of use. It involves deliberate and continuous adaptation processes, including Cognitive Understanding, which helps align diverse perspectives within implementation teams to create a shared understanding of the platform's capabilities, limitations, and potential use cases. Contextual Adaptation, which explains the need to tailor the platform's open-ended, context-agnostic architecture to the specific needs and workflows of the organization, ensuring that AI-based applications are relevant and effective. Infrastructure Compatibility Evaluation, which necessitates evaluation and reconfiguration of legacy systems, databases, and data structures, so they integrate seamlessly with the platform, enabling it to function as intended and scale effectively. By uncovering these essential steps, the model highlights the active role organizations must play to democratize AI in a meaningful way, transforming the narrative from a technology-driven approach to a sociotechnical perspective. The thesis further explains how implementing a low-code AI platform transforms organizations in qualitatively different ways (Holmström, 2022). These platforms are not merely tools for automation or efficiency; they fundamentally reshape how organizations operate, innovate, and collaborate. For example, the inclusion of non-technical users in AI application development fosters a more diverse, participatory approach to problem-solving, driving workforce transformation as both business and IT experts take on new responsibilities to ensure these dynamic systems remain relevant and continuously deliver value. Additionally, as illustrated in this thesis, organizations need to engage in process reengineering by rethinking and standardizing their business processes to align them with the platform's requirements and leverage its generative capabilities for continuous improvement. Finally, once the platform and its applications are operational, organizations transform through data-driven innovation because the platform's ability to gather and learn from end-user data enables organizations to modernize their products, services, and decision-making processes dynamically over time. The process model reframes implementation as an ongoing, iterative journey rather than a one-time event. It emphasizes that value creation with low-code AI platforms depends on the continuous alignment of the platform's capabilities with the evolving needs of the organization. This alignment fosters long-term opportunities for innovation and growth, illustrating that the true value of these platforms lies in their capacity to adapt and evolve in collaboration with the organizational environments they are embedded in.

By offering this process model, the thesis provides both theoretical and practical insights into what it takes to democratize AI and how the implementation of low-code AI platforms drives organizational transformation beyond efficiency gains, enabling innovation and long-term value creation.

Practical Implications

For organizations adopting low-code AI platforms to automate business processes through AI-based applications, this thesis provides several practical insights.

First and foremost, this thesis presents a conceptual process model that highlights the sociotechnical dynamics of low-code AI implementation. Although the scope of these insights is limited to large organizations, I believe small and medium-sized companies can also use this model as a practical guideline since the implementation process is the same, just on a smaller scale with fewer and less heterogeneous implementers, business processes to train the platform on, and backend systems and databases to evaluate and reconfigure.

The model's three adaptation processes can guide practitioners in addressing key implementation questions. In relation to *Cognitive Understanding* these questions include: What assumptions exist about low-code AI within the implementation teams? How can a common understanding of the platform's potential and limitations be fostered to ensure successful implementation? These questions can help practitioners align diverse perspectives, define implementation boundaries, and address the platform's open-ended nature. In relation to *Contextual Adaptation,* instead of perceiving low-code AI as a plug-and-play solution, practitioners should ask: How can the platform's context-agnostic nature be tailored to our specific business needs? What business processes need to be standardized and optimized to ensure the platform is trained with accurate and relevant data? In relation to *Infrastructure Compatibility Evaluation,* beyond relying solely on prebuilt interfaces, practitioners should assess: What data sources does the platform require? Are these data sources accessible and in the appropriate format, or do they need reconfiguration? Addressing these questions can better prepare organizations for seamless integration with existing backend systems and databases.

Second, the thesis also sheds light on the platform's role in shaping and facilitating adaptation processes. It reveals that low-code AI platforms push organizations to rethink their workflows and embrace greater flexibility to leverage the platform's open-ended, malleable nature. Before value creation can occur, organizations must explore and adapt their practices to align with the platform's capabilities. Moreover, once the platform is operational, its capacity to leverage data enables continuous growth in functionality and the modernization of business products, processes, and services. By gathering and learning from end-user data, the platform helps organizations evolve and innovate over time.

Third, this thesis cautions against a narrow focus on efficiency gains and cost reduction typically associated with low-code AI application development. Instead, it emphasizes the distinction between short-term and long-term value paths. While initial efficiency improvements may be realized, the true potential of generative systems like low-code AI lies in their long-term value. Continuous data gathering, learning, and iterative improvements enable organizations to unlock opportunities for sustained innovation and growth. Thus, the implementation of low-code AI platforms should not be viewed as a one-time event that guarantees value creation. Rather, it is an ongoing sociotechnical adaptation process requiring continuous alignment between the platform’s IT capabilities and the organization’s evolving environment. Only through sustained efforts can organizations fully leverage the transformative potential of low-code AI platforms for value creation.

Finally, for platform developers, this thesis highlights the need to reevaluate how low-code AI platforms are marketed. These solutions are often advertised as ready-to-go tools capable of democratizing AI application development and unlocking significant value creation for implementing organizations. However, this thesis illustrates that such narratives can create unrealistic expectations, leading to frustration when the anticipated value remains unrealized. To address this, platform developers should shift their messaging to emphasize the importance of the platforms' sociotechnical embedding and their dependence on adaptation processes that need to continuously align and grow the platform’s capabilities and the organizational environments in which they operate. This reframing would better align expectations with the realities of low-code AI implementation, cultivating more sustainable and effective adoption of such generative systems.

5.5 Limitations of Scope & Future Research

In addition to the methodological limitations discussed in Section 3, this thesis has limitations of scope, i.e., intentional boundaries around the study’s focus that define what the research does and does not cover. These limitations arise from practical constraints related to time, resources, and feasibility, as well as strategic choices made to keep the study manageable and focused. Specifically, the primary limitations of scope are *(1) the focus on a single platform, (2) the emphasis on large, well-established organizations, and (3) temporal limitations.*

First, this thesis centers on the implementation of one specific low-code AI platform within eight large organizations across multiple industries. While this single-case design allows for an in-depth exploration of the platform’s generative capabilities and their impact on value creation, it also limits the generalizability of findings to other platforms. Although the case study approach is not intended to yield broad generalizations (Yin, 2018), future research could include comparative studies across multiple low-code AI platforms to provide a more comprehensive understanding of their value creation.

Second, this thesis focuses on large, well-established companies within specific industries, namely energy, automotive, retail, telecommunications, and hospitality. While the findings may still offer valuable insights for smaller firms, they may not face the same critical challenges as larger organizations. Large organizations contend with a diverse pool of actors, complex and entrenched business processes, and outdated legacy systems, factors that may be less prominent in smaller firms. Exploring different organizational contexts in future research could further enrich our understanding of how diverse environments impact the implementation and value creation of low-code AI platforms.

Lastly, this thesis has temporal limitations in examining multi-year implementation processes across the studied organizations, capturing a broad timeline of their engagement with the platform. However, since it primarily relies on retrospective data from interviews, it does not provide a sequential view of long-term impacts or the ongoing evolution of value-creation processes as organizations continue to learn, update models, and add functions. Future longitudinal studies could offer deeper insights into the sustained effects of low-code AI platforms on organizational performance and strategic adaptation over time.

6. Conclusion

This thesis explores how large organizations pursue value creation through low-code AI platforms, illustrating the complexities of implementing generative systems within established business contexts. By examining the iterative and ongoing nature of these platforms' implementation, this research challenges traditional, linear perspectives on IS implementation. It demonstrates that, unlike conventional systems with limited functionality and a specific outcome, low-code AI platforms evolve continuously, requiring organizations to engage in dynamic sociotechnical processes of adaptation.

Through an embedded case study of a specific low-code AI platform, this research reveals that generative systems operate differently from conventional IT systems, such as ERP, offering unique affordances and constraints that influence organizational use. The thesis argues that the true value of such platforms emerges not immediately, but through long-term investment and the iterative accumulation of data and user engagement. This perspective reframes implementation as a fluid and iterative process, where the platform's generative architecture supports ongoing adaptation to diverse business needs, unlocking innovative paths to value creation over time.

The process model introduced here provides a structured understanding of how large organizations interact with low-code AI platforms, highlighting the sociotechnical dynamics of key adaptation processes that sustain generativity and facilitate diverse value paths. This model captures the dynamic relationship between technology, users and their organizational environments, emphasizing that effective implementation is an evolving journey rather than a static achievement.

In conclusion, this thesis underscores the need for organizations to approach low-code AI platforms with a long-term view, recognizing that their potential lies in sustained engagement and continuous adaptation. The findings contribute to a deeper understanding of generative systems within IS literature, offering insights that will benefit both researchers and practitioners as they navigate the transformative potential of low-code AI platforms in organizational contexts.

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