Please quote as: Bruhin, O., Ebel, P. & Bauer-Hänsel, I. (2025). Unlocking Business Value with Generative AI: Balancing Co-Creation and Co-Destruction in Knowledge Work. Proceedings in the Thirty-Third European Conference on Information Systems (ECIS), Amman, Jordan.

June 2025

Unlocking Business Value with Generative AI: Balancing Co-Creation and Co-Destruction in Knowledge Work

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UNLOCKING BUSINESS VALUE WITH GENERATIVE AI: BALANCING CO-CREATION AND CO-DESTRUCTION IN KNOWLEDGE WORK

Completed Research Paper

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Abstract

This study investigates the dual impact of Generative AI tools on business value in knowledge work, focusing on value co-creation and co-destruction. Drawing from three case studies across diverse industries and over a year of GenAI integration, we analyzed qualitative insights from 15 industry experts. We contextualized our insights using the value co-creation and co-destruction framework and the value discipline lens. Our findings reveal GenAI's nuanced role in enhancing operational efficiency, enabling innovative solutions through supporting complex problem-solving and more creative employee engagement, and strengthening customer intimacy through mechanisms such as depth or availability of the interaction. However, risks such as over-reliance on AI, quality concerns, and the erosion of critical human judgment skills complicate its adoption. By balancing these perspectives and explaining the value creation logic, this study provides a nuanced understanding of GenAI's role in shaping business value, offering actionable recommendations for effective and sustainable integration.

Keywords: Generative AI, Knowledge Work, Value Co-Creation, Value Co-Destruction, Impact

1 Introduction

Generative Artificial Intelligence (GenAI) has emerged as a transformative innovation, particularly in the domain of knowledge work, where it holds the potential to enhance productivity, creativity, and strategic decision-making (Dell'Acqua et al., 2023; Mariani & Dwivedi, 2024). Unlike traditional AI systems, which primarily focus on analysing and predicting outcomes from predefined data, GenAI introduces a fundamentally new paradigm by generating novel content, ideas, and solutions. This generative capability has far-reaching implications for knowledge-intensive fields such as marketing, software development, health care and education to rate accelerate operations, enhance innovation and drive business value across the whole field (Shollo et al., 2022; Retkowsky et al., 2024).

Knowledge work refers to professional activities that are primarily cognitive, non-routine, and creativity-driven, requiring expertise, problem-solving, and continuous adaption to new information (Hislop, 2018). Unlike routine labour, knowledge work is characterized by intellectual complexity, decision-making under uncertainty, and the integration of domain-specific knowledge into strategic or problem-solving processes. Knowledge work includes a wide range of professional areas, such as marketing, software development, health care and education (Kuusisto & Meyer, 2003).

With the rise of Artificial Intelligence (AI) and GenAI, knowledge work is undergoing a transformation in the entire work system where AI can automate repetitive cognitive tasks, augment human capabilities, and reshape creative and decision-making processes (Bruhin, 2024). Historically, knowledge work was considered resistant to automation due to its reliance on tacit knowledge, intuition, and contextual understanding (Lacity & Willcocks, 2016). However, advancements in GenAI now enable automation

in areas such as marketing, software development (Bruhin et al., 2024; Brynjolfsson et al., 2023), health care (Gupta et al., 2021), and education (Rudolph et al., 2023), altering the balance between human expertise and machine-generated insights (Brynjolfsson et al., 2023). Prior research has focused on exploring productivity and efficiency gains from GenAI integration in knowledge work (e.g., Brynjolfsson & McAfee, 2016; Shollo, et al., 2022; Retkowsky et al., 2024; Hislop, 2018). Despite its promises, there is still a lack of clarity around the dual impact of GenAI on knowledge work – how it not only generates value but also may introduce inefficiencies, risks, or unintended consequences. This ambiguity makes it challenging for organizations to assess whether GenAI genuinely improves decision-making and problem-solving or simply adds new layers of complexity and potential disruption. Additionally, rising costs associated with untargeted GenAI development (Kaddour et al., 2023) highlight the need for a clearer understanding of where and how GenAI investments generate value. Without this understanding, organizations risk misallocating resources failing to capture real business benefits, or even experiencing value destruction, and struggle with expanding IT costs.

This study addresses these gaps by investigating both the enabling and constraining effects of GenAI on business value creation in knowledge work. Specifically, we explore how GenAI contributes to value co-creation and value co-destruction in knowledge work. Our research is motivated by practical challenges observed in real-world implementations, as well as by conceptual and empirical gaps in the existing literature. To achieve this, we pose the following research question:

RQ: *How does GenAI enhance and constrain business value creation in knowledge work?*

To address this question, we use a theory-elaborating case study (Ketokivi & Choi, 2014) across three organizations. All organizations considered in the study have at least one year of experience using GenAI, focusing on diverse knowledge work applications. Our study draws on 15 in-depth informal conversations with industry experts and applies two theoretical lenses: First, the lens of Value Co-Creation and Value Co-Destruction (Echeverri & Skålén, 2011) to assess both positive and negative effects of GenAI on business value creation. And second the Value Discipline Framework (Treacy & Wiersema, 1992), which provides a structured perspective to investigate how GenAI supports or constrains operational excellence, product leadership, and customer intimacy.

By providing a detailed analysis of GenAI's role in business value creation and destruction processes of GenAI's, this study offers both practical insights for organizations to optimize their GenAI investments and theoretical contributions to the understanding of GenAI's dual impact

This paper is structured as follows: First, we review related literature on GenAI's business value implications. Next, we outline the theoretical frameworks guiding our analysis and describe the methods used to collect and analyze data. Subsequently, we present our findings, followed by a discussion of implications, limitations, and directions for future research.

2 Theoretical Background

2.1 Creating Value through Generative Artificial Intelligence (GenAI)

GenAI represents a paradigm shift in knowledge work, where AI is no longer limited to analysing and predicting predefined data but actively contributes to content generation, creative augmentation, and decision support. Given that knowledge work is inherently cognitive, non-routine, and creativity-driven, requiring expertise, problem-solving, and continuous adaptation to new information (Hislop, 2018), the integration of GenAI presents both opportunities and challenges for business value creation. Historically, knowledge work was considered resistant to automation due to its reliance on tacit knowledge, intuition, and contextual understanding (Lacity & Willcocks, 2016). However, recent advancements in AI have enabled automation and augmentation in areas such as content creation, software development, pharmacology, consulting, and education, fundamentally altering the balance between human expertise and machine-generated insights (Kuusisto & Meyer, 2003; Brynjolfsson et al., 2023; Gupta et al., 2021; Rudolph et al., 2023).

One key area of value creation with GenAI lies in content generation and creativity, where GenAI's ability to produce novel text, images, and other media augments human capabilities (Dakhel et al., 2023).

This enables professionals to explore new creative directions and deliver unique, high-quality outputs at scale. For instance, marketing teams can leverage GenAI to generate personalized advertising campaigns, while product developers can explore alternative designs using AI-generated prototypes. These capabilities significantly broaden the creative bandwidth of teams and enhance their ability to innovate. Another critical dimension of GenAI's value is its role in fostering human-AI collaboration. Unlike earlier AI systems designed to assist with close-ended, task-specific objectives, GenAI creates opportunities for co-creation by working alongside humans in iterative processes. This dynamic not only enhances productivity but also supports complex problem-solving and innovation (Barke et al., 2023; Mehler & Krautter, 2024). For example, GenAI tools can propose solutions or generate ideas that human collaborators refine, creating outcomes that neither party could achieve alone.

GenAI's unique characteristics — such as its probabilistic output, general-purpose functionality, and ability to generate novel products and services — further differentiate it from traditional AI. These traits allow GenAI to impact domains beyond decision-making, extending its influence into areas like strategic planning, customer engagement, and product development (Berente et al., 2021; Sun et al., 2023). For example, generative capabilities enable organizations to deepen customer relationships through hyper-personalized interactions and recommendations, which were not achievable with previous AI models.

While GenAI shares foundational characteristics with traditional AI, such as autonomy, self-learning capabilities, and inscrutability, its generative nature requires a reevaluation of its role in value creation (Eloundou et al., 2023; Zhang et al., 2024). Traditional AI supports operational efficiency and decision-making by analyzing historical data, while GenAI enables the proactive creation of value through innovation-driven processes and knowledge expansion (Mehler & Krautter, 2024). This paradigm shift underscores the importance of studying more in-depth how GenAI's impact on business value unfolds and which attributes of the technology eventually enable or enhance business value creation.

2.2 Value Co-Creation and Value Co-Destruction

Considering recent pressing challenges faced by organizations – particularly the rising costs of GenAI development and the uncertainty around its actual value contribution – there is growing need to better understand the dual impact of GenAI on business value creation.

The integration of GenAI into knowledge work introduces a dual impact on business value, serving both as an enabler of value co-creation and a potential source of value co-destruction. Understanding this dual impact requires a structured theoretical approach. GenAI can both act as a catalyst for value co-creation and as a potential driver of value co-destruction in knowledge work. Addressing this complex dynamic requires a structured theoretical framework that captures not only the enabling aspects of GenAI but also the conditions under which it may constrain or undermine value creation. The theoretical lens of Echeverri & Skålén (2011) on value co-creation and value co-destruction provides a suitable framework for such an analysis. Applying this perspective allows us to explore how GenAI facilitates collaborative value generation while also accounting for the risks associated with the misuse, over-reliance, or misaligned implementation in knowledge work.

Value co-creation refers to the collaborative processes between stakeholders—such as employees, customers, and technology providers—through which resources, skills, and knowledge are pooled to generate mutual benefits (Echeverri & Skålén, 2011; Plé & Cáceres, 2010). In contrast, value co-destruction occurs when interactions between these stakeholders lead to negative outcomes, such as inefficiencies, diminished engagement, or other unintended consequences that detract from overall value (Järvi et al., 2018).

In the context of GenAI, value co-creation involves collaborative processes where employees, technology, and organizational structures synergize to produce mutual benefits. GenAI enables co-creation by augmenting employees' capacities, facilitating knowledge sharing across teams, and fostering enhanced productivity and collaboration. This perspective highlights how GenAI supports efficient and creative problem-solving, empowering employees to focus on strategic and complex tasks, rather than routine ones (Plé & Cáceres, 2010; Schulz et al., 2021). Moreover, GenAI's adaptable and

context-sensitive nature allows employees to shape its outputs, fostering ownership and engagement that are essential for sustained value creation.

In contrast, value co-destruction represents risks and negative outcomes that may arise when GenAI tools are misused or excessively relied upon, leading to diminished productivity and engagement. While GenAI can enhance efficiency, it also presents challenges, such as over-reliance on AI for decision-making, which can erode employees' critical thinking and problem-solving skills over time (Echeverri & Skålén, 2011; Järvi et al., 2018). Additionally, limitations inherent to GenAI, such as misinterpretations and costly errors if users fail to critically assess its suggestions.

Despite growing interest in value co-creation and co-destruction specifically to GenAI in organizational contexts, there is limited research applying such a dual view on productivity. Current literature often emphasizes either the productivity gains or technical capabilities of GenAI (Barke et al., 2023; Dell'Acqua et al., 2023; Liang et al., 2024; Mehler & Krautter, 2024), without addressing the nuanced, dual nature of value creation and destruction that arises when these tools are integrated into complex organizational environments.

2.3 Business Value Disciplines

To better understand how GenAI enables or constrains organizations in their ability to create and sustain business value, we build on the value disciplines framework, first introduced by Treacy & Wiersema (1992). This framework identifies three core value disciplines that companies can prioritize to gain competitive advantage: Operational Excellence, Product Leadership, and Customer Intimacy. Each of these disciplines provides a strategic lens through which organizations can evaluate where and how GenAI contributes to business value creation. By integrating GenAI into these dimensions, organizations can align AI adoption with their overarching strategic goals, optimizing its potential while mitigating associated risks – particularly those linked to potential value co-destruction, such as its misuse, over-reliance, or misaligned implementation in knowledge work.

The first value discipline, Operational Excellence, focuses on streamlining processes, reducing costs, and improving productivity (Eichen, 2006). GenAI can support operational excellence by automating repetitive, high-volume tasks, thus allowing human resources to be reallocated to strategic areas (Moraes et al., 2022). This is particularly relevant for knowledge-intensive industries like software development, where AI tools can enhance developer efficiency by minimizing time spent on low-value tasks (Schmidt, 2023). Operational excellence as a value discipline helps organizations identify areas where GenAI can yield the greatest process improvements, ensuring that investments in AI contribute to overall organizational efficiency.

The second value discipline, Product Leadership, emphasizes innovation and differentiation, enabling organizations to create market-leading solutions that set them apart from competitors (Hagel & Singer, 1999). In this domain, GenAI serves as a key enabler of innovation by facilitating complex problem-solving, creative design processes, and advanced data-driven insights. For instance, in product development, GenAI assists in generating new ideas, optimizing design alternatives, and even predicting customer trends to enhance product-market fit. In industries such as pharmacology, media, and engineering, AI-driven models help professionals accelerate research, prototype new solutions, and identify emerging opportunities (Beheshti, 2023). Unlike traditional AI systems that focus on efficiency alone, GenAI fosters creativity and experimentation, allowing organizations to explore solutions beyond human cognitive limitations. Through this, organizations can leverage GenAI not just for productivity gains but as a core driver of sustained competitive advantage and differentiation (Osterwalder & Pigneur, 2010).

The third value discipline, Customer Intimacy, focuses on understanding and personalizing customer interactions to enhance relationships and long-term loyalty (Treacy & Wiersema, 1992). Through AI-driven analytics, sentiment analysis, and real-time response capabilities, GenAI enables organizations to engage with customers more effectively and tailor interactions to meet individual needs. In knowledge-intensive settings, where relationships and tailored service are crucial, customer intimacy as

a value discipline helps to identify how GenAI can enhance customer satisfaction and loyalty by providing responsive, personalized support (Bauer et al., 2019).

While empirical evidence suggests that GenAI facilitates value creation and enhances competitive advantage across these three value disciplines, its role in value co-creation and potential value co-destruction remains insufficiently explored. Consequently, both practice and academia lack critical insights into the specific considerations required when developing GenAI applications, as well as the distinctive attributes that a GenAI co-creator should possess to effectively support the value creation process.

3 Research Method

3.1 Methodology

In this research, we employ a theory-elaborating case study approach following Ketokivi & Choi (2014) to explore the impact of GenAI tools in organizations across different industries that have been using GenAI tools to increase their competitiveness for more than a year. Case study research is particularly well-suited for investigating complex phenomena within real-life contexts, as it allows for an in-depth exploration of processes, perceptions, and interactions (Yin et al., 2018). By analysing companies from telecommunication and software development, finance, and insurance sectors—referred to as TeleComp, FinanComp, and InsurComp—we aimed to gain a comprehensive understanding of how GenAI tools enable or constrain business value creation that recognized domain cross-case patterns and avoid single-sided impressions (Eisenhardt, 1989).

3.2 Data Collection

Between January 2024 and October 2024, we conducted in-depth, informal conversations (Swain & King, 2022) with 15 industry experts working in organizations based in Central Europe. By using informal conversations within the context of research-practice collaborations, we created a comfortable setting that encouraged participants to naturally share nuanced insights (Swain & King, 2022) about their experiences with GenAI tools. Unlike formal interviews, informal conversations create a more relaxed environment that encourages participants to share insights beyond structured prompts. As Warren et al. (2003, p. 107) describe, valuable information often emerges “after the interview” when the recording device is off, as participants feel less restricted and speak more openly. This highlights the importance of a naturalistic approach to data collection, where informal conversations are a valuable alternative to interviews, capturing unfiltered insights that might otherwise remain unspoken. The participants represented a range of roles, including IT Managers, IT Executives, IT Operations Analysts, Product Owners, Platform Architects, and Solution Train Engineers, ensuring diverse perspectives across multiple levels of expertise.

The informal conversations took place over multiple iterations, with each participant contributing a total of 120 and 300 minutes, across multiple sessions, allowing them to share detailed, in-depth experiences with GenAI tools. Throughout the discussions, During the series of conversations, the researchers ensured alignment with the study’s objective by steering the discussions through targeted questions. They also took extensive notes and created transcripts to support the analysis and maintain focus on the study’s aims throughout.

We opted for three distinct cases from different knowledge-intensive industries, namely telecommunication and software development, financial services, and insurance (Yin et al., 2018). Each of the organizations has at least one year of experience using GenAI tools. By integrating insights from multiple cases and a variety of expert roles, this approach enabled us to obtain in-depth insights, enhancing both the validity and generalizability of the exploratory findings (Eisenhardt, 1989).

Table 1 provides an overview of the collected material. To comply with data protection agreements established with participating partners, the participants have been anonymized, though their roles, affiliated organizations, and the estimated total time spent in the conversations are disclosed.

Case Company	Participant ID	Role in Organization	Discussion Time (approx. in min.)
TeleComp	I1	IT Manager	140
	I2	IT Manager	120
	I3	IT Operations Analyst	165
	I4	IT Executive	245
	I5	Product Owner & Platform Architect	300
FinanComp	I6	IT Manager	150
	I7	Release Train Engineer	125
	I8	IT Executive	180
	I9	DevOps Engineer	140
	I10	Product Owner	249
InsurComp	I11	IT Manager	200
	I12	IT Executive	180
	I13	Product Owner	130
	I14	Solution Train Engineer	120
	I15	IT Manager	155

Table 1. Overview of the industry experts.

3.3 Data Analysis

To analyse our data, in the first step, we performed open and axial coding of our interview data following Strauss & Corbin (1998) to uncover concepts and dimensions in our data to detect patterns in the underlying interview data. Next, we reviewed our codes, identified relationships, and grouped them into categories, considering how these categories might be linked and to help reveal overarching themes (Krippendorff, 2004). We applied this method to categorize the key insights we obtained from the informal conversations with our 15 industry experts.

In the second step, we aligned the emergent categories with the guiding theoretical frameworks following a theory-elaboration approach (Ketokivi & Choi, 2014) to redefine and extend the existing theoretical concepts. Rather than developing a new theory, we used these frameworks as analytical tools to structure our findings, identify new nuances, and contextualize the role of GenAI in business value creation. Specifically, we used the Value Discipline Lens Treacy & Wiersema (1992) and the Value Co-Creation and Co-Destruction Lens based on Echeverri & Skålén (2011). This mapping process allowed us to contextualize the categories within the dual roles of GenAI: its ability to enhance value creation and its potential to constrain value realization.

Table 2 provides an illustrative example of the content analysis performed in this study.

Illustrative Data	Category
Quote I2: *"With automation through AI, I save 80% of working time."*	Task Removal
Quote I5: *"GenAI takes care of routine tasks, allowing our team to focus on high-value work that demands critical thinking and problem-solving."*	Workload Reduction
Quote I12: *"AI is great for repetitive tasks, but when applied to complex situations without human judgment, it risks creating costly errors that can be hard to undo."*	Contextual Human Judgement
Quote I11: *"AI can be a boost on productive days but a hindrance on less productive days."*	Productivity Variability

Table 2. Illustrative example of the content analysis.

Additionally, we conducted a cross-case comparison to enhance the robustness and transferability of our findings. The content analysis process was carried out by one author, who was responsible for the initial coding, while the other authors reviewed and validated the coding scheme to ensure external validity and minimize potential bias. Following Yin et al. (2018), examining multiple case studies strengthens the reliability and application of research outcomes across diverse contexts. By identifying similarities and differences across organizational settings, we were able to generalize key themes while acknowledging the unique contexts of each case (Patton, 1990). Despite variations among the organizations studied, the cross-case analysis revealed consistent patterns, contributing to a robust and validated understanding of GenAI's impact on knowledge work.

This combined approach of inductive content analysis, theoretical mapping, and cross-case comparison allowed us to provide a nuanced, qualitative understanding of how GenAI contributes to value creation and where it may lead to value co-destruction. The theoretical frameworks served not only as analytical tools but also as lenses to categorize and interpret GenAI's dual roles in enabling and constraining value outcomes.

4 Results

The results of our qualitative cross-case analysis highlight the dual impact of GenAI on business value in the categories operational excellence, product leadership, and customer intimacy. This shows how GenAI has the potential to both enhance and reduce business value. Table 3 provides a summary of our findings, which are described in detail in the following subsections.

Dimension	GenAI Value Co-Creation	GenAI Value Co-Destruction
Operational Excellence	**Task Removal** Value is created when GenAI automates repetitive, process-driven tasks, freeing employees to apply their contextual understanding and decision-making skills. The combination of machine efficiency and human strategic oversight enhances overall productivity and cost-effectiveness.	**Contextual Human Judgement** Value is destructed when GenAI is used for nuanced tasks that require human judgment, and human oversight fails to correct AI-generated errors. The lack of synergy between AI's capabilities and human intervention leads to costly mistakes and lost productivity.
	Workload Reduction By handling simpler components of a task, GenAI creates space for professionals to focus on higher-level or new responsibilities. The interplay between AI-driven support and human creativity enables a more comprehensive approach to productivity and innovation.	**Productivity Variability** Inconsistent collaboration between employees and GenAI can result in fluctuating productivity levels. Misaligned expectations, unclear task delegation, or over-reliance on the AI can hinder stable performance, reducing overall efficiency.
Product Leadership	**Complexity Increase in Problem-Solving Capability** Teams leverage GenAI's ability to process vast amounts of data and generate insights while applying their own domain expertise and critical thinking to refine and implement solutions. The collaboration unlocks innovative, forward-thinking approaches to product development that neither could achieve alone.	**Quality Risks** Over-reliance on GenAI in critical tasks, combined with insufficient human input, can degrade the quality of outputs. When humans fail to compensate for GenAI's lack of nuanced understanding, the collaboration risks producing suboptimal results that harm overall outcomes.
	Creative Employee Engagement When GenAI takes over monotonous and routine tasks, employees can channel their energy into high value, stimulating work.	**Dependency on GenAI** Continuous reliance on GenAI for problem-solving diminishes employees' engagement with complex tasks, leading to a gradual

	This balance of AI efficiency and human creativity fosters better engagement, enabling teams to achieve higher-quality and more impactful results.	loss of critical thinking skills. The resulting dependency undermines the human side of the collaboration, limiting adaptability and professional growth.
Customer Intimacy	**Availability of Customer Services** GenAI provides 24/7 availability for immediate and consistent customer service, while humans step in to manage complex or emotionally sensitive situations. The partnership ensures faster responses without sacrificing personalized and empathetic problem-solving.	**Loss of Customer Connection** When customer interactions are overly delegated to GenAI, employees lose opportunities to engage meaningfully with customers. This weakens the personal connection, eroding trust and reducing the overall value created in the relationship.
	Depth of Customer Satisfaction GenAI analyses customer data to deliver personalized recommendations and responses, while employees build on these insights to deepen the emotional connection and trust with the customer. The synergy between machine-generated precision and human relational skills enhances loyalty and satisfaction.	**Loss of Empathic Problem-Solving Skill** Excessive use of GenAI in customer-facing tasks minimizes employees' involvement in addressing emotional or complex customer needs. Over time, this interplay diminishes their problem-solving skills and emotional intelligence, leading to a gradual erosion of deep customer relationships.

Table 3. Overview of GenAI Value Co-Creation and Co-Destruction.

4.1 GenAI Value Co-Creation

4.1.1 Operational Excellence

GenAI drives value creation through the **removal of repetitive, process-driven tasks**, enabling employees to focus on strategic activities that require contextual understanding and decision-making. This synergy between machine efficiency and human oversight enhances productivity and cost-effectiveness. For instance, an IT manager at FinanComp noted, *"With automation through AI, I save 80% of working time."* By reallocating routine tasks to GenAI, organizations optimize resource allocation and unlock new levels of operational efficiency.

GenAI tools can also support employee productivity through **workload reductions.** Through its ability to manage simpler aspects of tasks, GenAI fosters an environment where professionals can focus on high-level responsibilities or explore new opportunities. This balance between AI-driven support and human creativity boosts productivity and innovation. A Product Owner & Platform Architect at TeleComp highlighted this interplay, stating, *"GenAI takes care of routine tasks, allowing our team to focus on high-value work that demands critical thinking and problem-solving. This shift not only boosts our productivity but also lightens the mental load, letting us engage more deeply with complex tasks."*

4.1.2 Product Leadership

GenAI's ability to process large datasets and generate insights **enhances complex problem-solving capabilities** when paired with human domain expertise and critical thinking. This collaboration unlocks innovative, forward-thinking solutions for product development. An IT manager at FinanComp explained, *"With AI, I want to solve problems that are not solvable without it."* This complementary relationship ensures organizations can remain competitive by addressing complex challenges effectively.

By automating monotonous and routine tasks, GenAI allows employees to focus their efforts on stimulating, high-value activities. This balance fosters **creative employee engagement** and leads to higher-quality and impactful results. An IT Executive at InsurComp emphasized the importance of meaningful work, stating, "*My task as a manager is to keep my people fit in their mind for future*

technologies." The interplay between AI efficiency and human creativity empowers teams to thrive in dynamic and innovative environments.

4.1.3 Customer Intimacy

GenAI's 24/7 **availability of customer services** enhances the company's responsiveness, providing immediate support while freeing employees to manage complex or emotionally sensitive situations. This partnership between AI consistency and human empathy ensures seamless and personalized service. An IT Manager at TeleComp explained, *"The fact that AI can handle requests anytime adds a layer of reliability our clients appreciate. They feel assured that support is there when they need it, no matter the time."* This responsiveness aligns well with increasing customer demands for immediate support, making GenAI a valuable asset in maintaining strong customer relationships.

GenAI's ability to analyse customer data facilitates personalized recommendations and interactions, creating opportunities for employees to **deepen customer satisfaction** and build a more personal connection. This collaboration enhances loyalty and satisfaction. A Product Owner at InsurComp noted, *"Our AI system picks up on customer sentiments and tailors responses accordingly, which helps build trust and makes our clients feel understood."* This synergy between AI-driven insights and human engagement strengthens brand affinity, ensuring long-term customer loyalty and a competitive edge in the market.

4.2 GenAI Value Co-Destruction

4.2.1 Operational Excellence

Business value can be compromised when GenAI is applied to tasks that require nuanced human judgment but lack sufficient oversight. This **loss in contextual human judgement** can lead to significant errors and reduced productivity, ultimately leading to costly corrections. An IT Executive at InsurComp explained, "*AI is effective for repetitive tasks, but when applied to complex situations that need human oversight, it risks introducing costly errors that are difficult to correct."*

Productivity variability can arise as a co-destructive outcome when GenAI is used for tasks requiring nuanced judgment without sufficient human oversight, leading to errors that disrupt workflows and productivity. On days when employees are fully engaged, GenAI can amplify their performance by effectively supporting their efforts. However, as an IT Manager at InsurComp explained, *"AI can be a boost on productive days but a hindrance on less productive days."* When focus or decision-making is compromised, GenAI-generated outputs that lack the required contextual sensitivity may demand additional scrutiny and corrections, increasing cognitive load instead of easing it. This lack of synergy between AI capabilities and human intervention not only introduces inefficiencies but also creates frustration among employees, making it difficult to maintain stable workflows and consistent performance.

4.2.2 Product Leadership

Over-reliance on GenAI for tasks requiring nuanced judgment can **threaten product quality**. When critical tasks lack sufficient human oversight, the risk of errors increases, potentially compromising the integrity of outputs. For example, employees at FinanComp admitted to being "*overly dependent on ChatGPT,"* which resulted in mistakes during complex coding processes. This underscores the essential role of human intervention in ensuring AI-generated results align with organizational standards. Without this balance, product quality, customer satisfaction, revenue, and the company's reputation can be negatively affected.

Another risk to product leadership is the potential **dependency on GenAI**, which may diminish employees' problem-solving abilities. As employees increasingly rely on GenAI for generating ideas or tackling complex tasks, they may become less inclined to brainstorm independently or develop unique solutions, leading to a decline in their critical thinking and adaptability. An IT Manager at InsurComp highlighted this concern, explaining: "*If we rely too much on AI, we risk losing the creative drive and*

problem-solving skills that come from independent thinking". This dependency could ultimately reduce team resilience, as employees may feel less equipped to handle challenges on their own, undermining the organization's long-term adaptability and innovation capacity.

4.2.3 Customer Intimacy

Excessive delegation of customer interactions to GenAI weakens personal connections, reducing trust and loyalty. An IT Manager at FinanComp remarked, "We're at risk of losing customer connection when AI handles personal interactions." Maintaining a balance between AI efficiency and human engagement is critical for preserving customer relationships.

The delegation of customer interactions to GenAI is not without challenges in maintaining genuine customer connections. Outsourcing key touchpoints to GenAI risks **losing customer connection** between customers and employees. which is vital for building lasting relationships. An IT Manager at FinanComp emphasized, *"We're at risk of losing customer connection when AI handles personal interactions*," This highlights the delicate balance required to maintain personal customer intimacy while leveraging GenAI to gain depth into the intimacy.

Overuse of GenAI in customer-facing roles can reduce employees' involvement in addressing complex or emotionally sensitive issues. This can negatively impact their problem-solving abilities and emotional intelligence, leading to a **loss in human problem-solving skills**. A Product Owner at InsurComp shared, "*As we rely more on AI for customer issues, I'm concerned our team is losing the ability to think critically and connect with customers on a personal level."* This loss diminishes the organization's ability to maintain deep and meaningful customer relationships.

Figure 1 provides an overview of how humans and GenAI contribute to a company's business value.

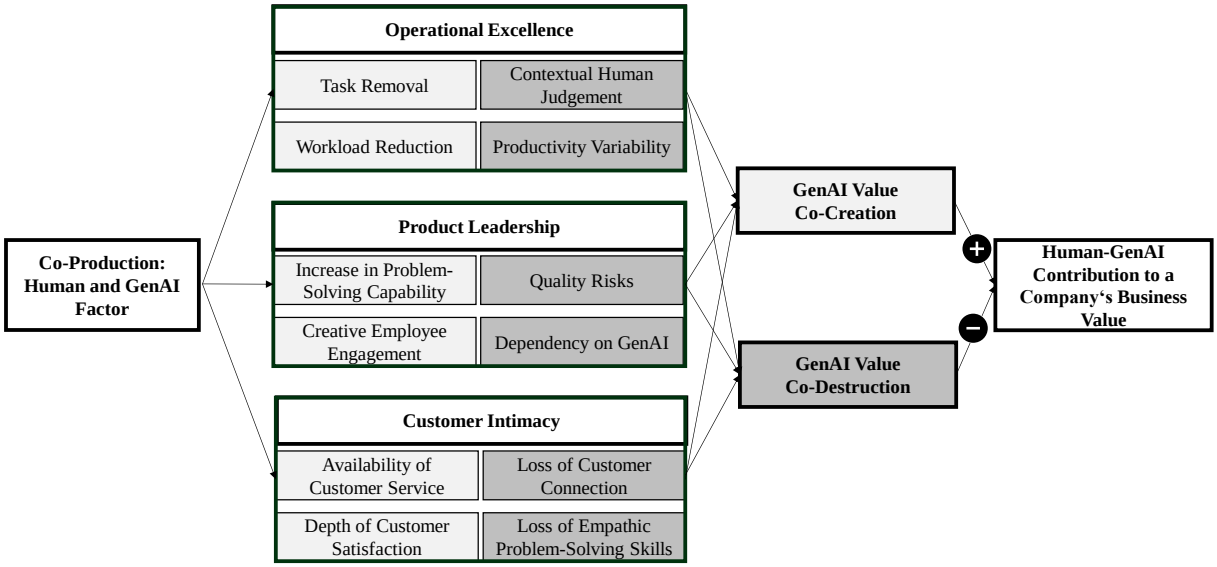

Figure 1. GenAI-enabled Value Co-Creation and Co-Destruction.

5 Discussion

This study sheds light on the complex, dual impact of GenAI on business value by systematically examining both value co-creation and co-destruction within knowledge work. Our study extends existing research, which has primarily explored GenAI potential to enhance productivity and innovation, as well as its benefits in automating routine tasks and reducing operational costs from a general perspective (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023; Li et al., 2024). With our study, we provide a more nuanced understanding of *how* GenAI creates and constrains value across three strategic dimensions: Operational excellence, product leadership, and customer intimacy. Specifically, our

findings align with previous studies, confirming that GenAI facilitates operational excellence by automating repetitive processes and allowing employees to concentrate on strategic tasks. Moreover, our study extends the understanding of GenAI's role in product leadership by illustrating how AI-driven tools can foster innovative solutions, namely by supporting complex problem-solving and contributing to more creative employee engagement. Thus, with our study, we provide a more nuanced in in-depth understanding of the how these rather general outcomes (operational efficiency, product leadership and customer intimacy) are achieved.

In the context of **operational excellence**, our findings confirm that GenAI drives productivity gains by automating and augmenting repetitive tasks, allowing them to focus on strategic and high-value activities. This process improves operational efficiency through two key mechanisms: workload reduction—where GenAI augments tasks to lighten the load on employees, increasing productivity—and task removal, in which GenAI fully automates certain processes, freeing employees to dedicate time to other critical areas. However, this same automation introduces risks of loss of contextual human judgement, as critical contextual judgments may be overlooked when tasks are entirely automated. Furthermore, variability in productivity arises when employees struggle to adapt to the interplay between AI-driven outputs and their own workflows, which can lead to inconsistent performance and frustration. It is important to note that while GenAI often acts as a co-creator by augmenting human work, in some cases, tasks are entirely handed over to GenAI. This transfer of competencies shifts responsibility from humans to AI, which is efficient in certain contexts but may reduce opportunities for collaborative value creation.

In terms of **product leadership**, GenAI enables organizations to solve more complex challenges and enhance creativity by broadening the scope of what teams can achieve. GenAI supports innovative solutions by processing vast datasets and offering insights that human teams can refine and implement. Employees also benefit from engaging in more meaningful, creative tasks as GenAI handles routine responsibilities. However, these opportunities come with risks, including quality at risk — where over-reliance on GenAI can compromise outputs if human oversight is insufficient — and dependency on GenAI, which can diminish employees' critical thinking and problem-solving abilities over time. The role of GenAI as a co-creator is particularly evident in product leadership, where collaboration between human expertise and AI-generated insights drives innovation. However, when employees become overly dependent on GenAI, the balance shifts from co-creation to a full transfer of creative responsibilities, which may hinder human adaptability in the long term.

In the domain of **customer intimacy**, GenAI's generative nature allows for greater depth of personalized services and enhances availability, enabling 24/7 support that strengthens customer relationships in ways that previous, discriminative AI systems could not achieve. By combining AI-driven precision with human empathy, organizations can deliver tailored interactions and foster deeper trust and loyalty. However, over-delegation of customer interactions to GenAI risks a loss of connection, weakening the personal relationships essential for long-term customer loyalty. Additionally, overuse of GenAI in customer-facing roles can erode employees' empathic problem-solving skills, reducing their ability to address emotionally or contextually sensitive issues effectively. Here, too, GenAI can act either as a co-creator, enhancing employee capabilities in delivering personalized services, or as a full substitute, taking over tasks entirely. While the latter approach is efficient, it may undermine the collaborative aspects of value creation between humans and AI.

This study also highlights the broader implications of GenAI's generative nature, which differentiates the value creation logic from traditional AI. Unlike prior discriminative AI models, GenAI can actively contribute to creativity, enabling organizations to achieve unprecedented levels of customization, innovation, and collaboration. For example, its ability to generate new ideas, content, or personalized responses enhances both operational and relational value, but this generative capacity also demands greater scrutiny to mitigate unintended consequences, such as errors in creative outputs or diminished employee engagement. However, the degree to which GenAI serves as a co-creator or as a standalone agent depends on the specific use case and the level of human involvement maintained in the process.

This research provides valuable contributions for both academia and practice.

For academic research, our findings contribute to the **Value Disciplines Lens** (Treacy & Wiersema, 1992) by demonstrating how GenAI supports and constrains the pursuit of operational excellence, product leadership, and customer intimacy. The study reveals that while GenAI facilitates co-creation by augmenting human capabilities, some interactions represent more of a delegation or outsourcing of tasks rather than genuine co-creation. For example, automation through GenAI often replaces human input entirely, creating efficiency but reducing opportunities for collaborative problem-solving and contextual judgment. Additionally, we extend the **Value Co-Creation and Co-Destruction Framework** (Echeverri & Skålén, 2011) by exploring the conditions under which co-creation or co-destruction occurs. Effective co-creation requires balanced human-AI collaboration, where employees actively shape AI-driven outcomes and maintain responsibility for quality. Conversely, co-destruction arises when this balance is disrupted—either through over-reliance on AI or insufficient integration of human oversight. By analyzing these dynamics, our study provides deeper insights into how organizations can maximize GenAI's co-creative potential while managing its co-destructive risks.

For practitioners, our findings present actionable insights into GenAI value co-creation and co-destruction, helping decision-makers in organizations make informed decisions about integrating GenAI effectively. Managers can use these insights to optimize the use of GenAI tools, enhance productivity while mitigating potential risks. Additionally, our proposed framework serves as a guide for balancing benefits and potential risks, enabling organizations to strategically adopt GenAI.

First, when developing GenAI prototypes, organizations should prioritize leveraging GenAI's unique capabilities to deepen customer interactions. Instead of deploying GenAI for generalized purposes, businesses should focus on harnessing its potential to deliver personalized and context-sensitive customer experiences, thereby strengthening customer loyalty and satisfaction. Second, co-destruction risks must be proactively managed. For instance, in the domain of product leadership, mitigating "quality risks" requires comprehensive employee training to prevent over-reliance on GenAI outputs. Employees should be encouraged to critically evaluate AI-generated content and maintain ultimate responsibility for decision-making, ensuring that human oversight upholds quality standards. Third, organizations should design GenAI adoption strategies that emphasize collaboration between human expertise and AI capabilities. By maintaining a human-in-the-loop approach, companies can enhance the co-creative potential of GenAI while preventing the erosion of critical human skills, such as problem-solving and creativity. By implementing these strategies, practitioners can maximize GenAI's value-creation potential while reducing its risks, fostering a more balanced and sustainable approach to integrating this transformative technology into organizational workflows. These approaches will also help managers effectively communicate the benefits and limitations of GenAI to stakeholders, paving the way for successful adoption and long-term competitive advantage.

6 Conclusion, Limitations and Outlook

In our study, we propose a conceptual framework that categorizes GenAI's dual impact into co-creation and co-destruction, linking these dynamics to operational, product, and customer outcomes. This framework provides a systematic foundation for examining GenAI's generative capabilities, particularly in knowledge-intensive fields.

While this study offers valuable insights into the dual impact of GenAI on business value in knowledge work, several limitations must be acknowledged. First, our research is based on a limited number of case studies within specific industries, potentially affecting the generalizability of our findings. Although we employed a cross-case analysis to enhance robustness, future studies should extend the research to a broader range of industries and organizational contexts to develop a more comprehensive understanding of GenAI's impact. Additionally, our study relied on informal discussions with industry experts as a qualitative method. While this approach provides rich, in-depth insights into participants' experiences, it may introduce biases related to subjective interpretations of GenAI's value. Future research could incorporate quantitative metrics to validate and expand on our findings, offering a more measurable assessment of GenAI's effects on productivity, decision-making quality, and customer engagement.

Another limitation lies in the focus on organizations with over a year of experience with GenAI tools. This scope may overlook the challenges and learning curves faced by companies in earlier stages of adoption. Longitudinal studies tracking the evolution of GenAI's role over time could yield valuable insights into how its impact on co-creation and co-destruction evolves as organizations mature in their use of the technology.

Looking ahead, future studies could refine and extend the proposed framework by developing quantitative metrics for the dimensions identified, providing a clearer understanding of how each contributes to business value creation and destruction. Additionally, further research could examine the interplay between these dimensions, deepening our understanding of their bundled nature and collective influence on organizational outcomes. This would help organizations to better navigate the dual impact of GenAI, maximizing co-creation and mitigating co-destruction risks.

Additionally, we recognize the potential to deepen the understanding of GenAI's role in knowledge work and business value creation by applying the theory of affordances, e.g. following the definition of Markus & Silver (2008). Investigating how GenAI shapes and limits action possibilities could provide valuable theoretical insights into how it functions as both an enabler and a constraint. This would allow for a more in-depth understanding of how human interaction with GenAI unfolds both as an enabler and a constraint. The affordance perspective would offer a nuanced understanding of how GenAI is not just a tool for automation but an active influence on how knowledge workers interact with technology, adapt their workflows, and derive value. This approach could help clarify the mechanisms through which GenAI fosters or hinders value co-creation and co-destruction.

Furthermore, future research should also incorporate the customer perspective in relation to customer intimacy within the business value disciplines framework. Understanding how GenAI enhances or constrains customer relationships and service personalization will provide deeper insights into its role in fostering customer engagement, trust, and satisfaction.

Beyond these aspects, another potential avenue for future research is to further examine the dynamics of human-GenAI collaboration. This would require a more detailed analysis of how GenAI's unique capabilities afford human action and how human responses co-constitute value creation and destruction. Investigating this interaction in greater depth could provide a richer theoretical foundation for understanding the mechanisms of co-creation and co-destruction, offering insights into how knowledge workers and AI shape outcomes together.

Ultimately, the goal is to advance this framework into a comprehensive model that not only illustrates the relationships between value co-creation and co-destruction but also provides actionable mechanisms for guiding GenAI's integration. Such a model would support practitioners in making informed, strategic decisions and communicating the benefits and limitations of GenAI to stakeholders, fostering sustainable and competitive adoption in knowledge-intensive industries.

References

Barke, S., James, M. B., & Polikarpova, N. (2023). Grounded Copilot: How Programmers Interact with Code-Generating Models. *Proceedings of the ACM on Programming Languages*, *7*. https://doi.org/10.1145/3586030

Bauer, I., Zavolokina, L., Leisibach, F., & Schwabe, G. (2019). Value Creation from a Decentralized Car Ledger. *Frontiers in Blockchain*, *2*. https://doi.org/10.3389/fbloc.2019.00030

Beheshti, A. (2023). Empowering Generative AI with Knowledge Base 4.0: Towards Linking Analytical, Cognitive, and Generative Intelligence. *2023 IEEE International Conference on Web Services (ICWS)*, 763–771. https://doi.org/10.1109/ICWS60048.2023.00103

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3). https://doi.org/10.25300/MISQ/2021/16274

Bruhin, O. (2024). Beyond Code: The Impact of Generative AI on Work Systems in Software Engineering Software Engineering. *Proceedings of the 45th International Conference of Information Systems (ICIS), Bangkok, Thailand*.

Brynjolfsson, E., Li, D., Raymond, L. R., Acemoglu, D., Autor, D., Axelrod, A., Dillon, E., Enam, Z., Garicano, L., Frankel, A., Manning, S., Mullainathan, S., Pierson, E., Stern, S., Rambachan, A., Reenen, J. Van, Sadun, R., Shaw, K., & Stanton, C. (2023). Generative AI at Work. *SSRN Electronic Journal*. *http://www.nber.org/papers/w31161*

Dakhel, A. M., Majdinasab, V., Nikanjam, A., Khomh, F., Desmarais, M. C., & Jiang, Z. M. (Jack). (2023). GitHub Copilot AI pair programmer: Asset or Liability? *Journal of Systems and Software*, *203*. https://doi.org/10.1016/j.jss.2023.111734

Dell'Acqua, F., McFowland, E., Mollick, E., Lifshitz-Assaf, H., Kellogg, K. C., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. *https://ssrn.com/abstract=4573321*

Echeverri, P., & Skålén, P. (2011). Co-creation and co-destruction: A practice-theory based study of interactive value formation. *Marketing Theory*, *11*(3), 351–373. https://doi.org/10.1177/1470593111408181

Eichen, M. (2006). Value Disciplines. A lens for successful decision making in IT. *EDUCAUSE QUATERLY*, 32–39.

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. In *The Academy of Management Review* (Vol. 14, Issue 4). https://www.jstor.org/stable/258557

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *http://arxiv.org/abs/2303.10130*

Gupta, R., Srivastava, D., Sahu, M., Tiwari, S., Ambasta, R. K., & Kumar, P. (2021). Artificial intelligence to deep learning: machine intelligence approach for drug discovery. *Molecular Diversity*, *25*(3), 1315–1360. https://doi.org/10.1007/s11030-021-10217-

Hagel, J., & Singer, M. (1999). Unbundling the corporation. *Harvard Business Review*, *77*, 133–144

Hislop, D. (2018). *Knowledge Management in Organizations: A Critical Introduction*. Oxford university press.

Järvi, H., Kähkönen, A. K., & Torvinen, H. (2018). When value co-creation fails: Reasons that lead to value co-destruction. *Scandinavian Journal of Management*, *34*(1), 63–77. https://doi.org/10.1016/j.scaman.2018.01.002

Kaddour, J., Harris, J., Mozes, M., Bradley, H., Raileanu, R., & McHardy, R. (2023). Challenges and Applications of Large Language Models. http://arxiv.org/abs/2307.10169

Ketokivi, M., & Choi, T. (2014). Renaissance of case research as a scientific method. *Journal of Operations Management*, *32*(5), 232–240. https://doi.org/10.1016/j.jom.2014.03.004

Kuusisto, J., & Meyer, M. (2003). Insights into services and innovation in the knowledge intensive economy. *Technology review*, *134*(2003).

Lacity, M. C., & Willcocks, L. P. (2016). A new approach to automating services. *MIT Sloan Management Review*, *58*(1), 41-49.

Li, M. M., Dickhaut, E., Bruhin, O., Wache, H., & Weritz, P. (2024). More Than Just Efficiency: Impact of Generative AI on Developer Productivity. *AMCIS 2024*.

Liang, J. T., Yang, C., & Myers, B. A. (2024, February 6). A Large-Scale Survey on the Usability of AI Programming Assistants: Successes and Challenges. *Proceedings - International Conference on Software Engineering*. https://doi.org/10.1145/3597503.3608128

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, *175*, 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Markus, M. L., & Silver, M. (2008). A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole's Concepts of Structural Features and Spirit. *Journal of the Association for Information Systems*, *9*(10), 609–632. https://doi.org/10.17705/1jais.00176

Mehler, M., Krautter, K. (2024). Productivity vs. Purpose: Generative AI Enhances Task Performance but Reduces Meaningfulness in Programming. *ECIS 2024 Proceedings*.

Moraes, C. H. V. de, Scolimoski, J., Lambert-Torres, G., Santini, M., Dias, A. L. A., Guerra, F. A., Pedretti, A., & Ramos, M. P. (2022). Robotic Process Automation and Machine Learning: a

Systematic Review. *Brazilian Archives of Biology and Technology*, *65*. https://doi.org/10.1590/1678-4324-2022220096

Osterwalder, A., & Pigneur, Y. (2010). Business model generation: a handbook for visionaries, game changers, and challengers. *John Wiley & Sons*.

Patton, M. Q. (1990). *Qualitative Evaluation and Research Methods*. SAGE Publications.

Plé, L., & Cáceres, R. C. (2010). Not always co-creation: Introducing interactional co-destruction of value in service-dominant logic. *Journal of Services Marketing*, *24*(6), 430–437. https://doi.org/10.1108/08876041011072546

Retkowsky, J., Hafermalz, E., & Huysman, M. (2024). Managing a ChatGPT-empowered workforce: Understanding its affordances and side effects. *Business Horizons*.

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching*, *6*(1), 342–363. https://doi.org/10.37074/jalt.2023.6.1.9

Schmidt, A. (2023). Speeding Up the Engineering of Interactive Systems with Generative AI. *Companion Proceedings of the 2023 ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, 7–8. https://doi.org/10.1145/3596454.3597176

Schulz, T., Zimmermann, S., Böhm, M., Gewald, H., & Krcmar, H. (2021). Value co-creation and co-destruction in service ecosystems: The case of the Reach Now app. *Technological Forecasting and Social Change*, *170*. https://doi.org/10.1016/j.techfore.2021.120926

Shollo, A., Hopf, K., Thiess, T., & Müller, O. (2022). Shifting ML value creation mechanisms: A process model of ML value creation. *Journal of Strategic Information Systems*, *31*(3). https://doi.org/10.1016/j.jsis.2022.101734

Strauss, A. L., & Corbin, J. M. (1998). Basics of qualitative research: techniques and procedures for developing grounded theory. *Sage Publications*.

Sun, W., Fang, Y., You, Y., Miao, Y., Liu, Y., Li, G., Deng, S., Huang, Y., Chen, Q., Zhang, H., Qian, Y., Liu, Y., & Chen, Z. (2023). Automatic code summarization via ChatGPT: How fare are we? *ArXiv:2305.13860*.

Swain, J., & King, B. (2022). Using Informal Conversations in Qualitative Research. *International Journal of Qualitative Methods*, *21*. https://doi.org/10.1177/16094069221085056

Treacy, M., & Wiersema, F. (1992). *Customer Intimacy and Other Value Disciplines*.

Warren, C. A. B., Barnes-Brus, T., Burgess, H., Wiebold-Lippisch, L., Hackney, J., Harkness, G., Kennedy, V., Dingwall, R., Rosenblatt, P. C., Ryen, A., & Shuy, R. (2003). After the interview. *Qualitative Sociology*, *26*(1), 93–110. https://doi.org/10.1023/A:1021408121258

Yin, R. K., Calvin, Y., & Mali, G. (2018). *Case Study Research and Applications: Design and Methods*. https://doi.org/http://dx.doi.org/10.1563

Zhang, X., Xu, T., Wei, X., Tang, J., & Ordonez de Pablos, P. (2024). The establishment of transactive memory system in distributed agile teams engaged in AI-related knowledge work. *Journal of Knowledge Management*, *28*(2), 381–408. https://doi.org/10.1108/JKM-10-2022-0791