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MESTRADO EM CIÊNCIA DA INFORMAÇÃO

The Impact of Generative AI on Knowledge Management Processes within Organizations

Rosalina Silva

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2025

UNIDADES ORGÂNICAS ENVOLVIDAS

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Mestrado em Ciência da Informação

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June 30, 2025

Resumo

A rápida emergência da Inteligência Artificial Generativa (GenAI) significa uma profunda mudança de paradigma na forma como as organizações gerem, criam, disseminam e aplicam o conhecimento. Uma breve revisão da literatura contemporânea revela que, embora a GenAI ofereça oportunidades significativas para aprimorar os processos de gestão do conhecimento (GC) através das suas capacidades em gerar conteúdo, automação de tarefas cognitivas e processamento de dados complexos, a sua integração eficaz em contextos organizacionais continua a ser um desafio crítico. Isto deve-se, em grande parte, a uma compreensão subdesenvolvida das interdependências da GenAI com disciplinas fundamentais como a Gestão da Informação (GI), a Gestão de Dados (GD) e a Governança de Dados (GovD), que são primordiais para garantir a qualidade dos dados, a otimização operacional e o alinhamento estratégico. Além disso, existe uma lacuna no discurso académico relativamente a um quadro abrangente e sociotecnico que aborde as dimensões humanas, organizacionais e éticas da implementação da GenAI em ambientes intensivos em conhecimento.

Reconhecendo esta necessidade crítica, esta dissertação adopta um paradigma de investigação em Design Science Research (DSR) para desenvolver um novo quadro conceptual: o Generative AI-Enhanced Knowledge Management Framework (GAKMF). Este quadro capta o impacto multifacetado da GenAI nos processos centrais de GC — especificamente, a criação, o armazenamento e recuperação, a transferência e partilha, e aplicação do conhecimento — enquanto situa rigorosamente esta transformação nos domínios interligados da GI, GD e GovD. A investigação envolve uma revisão crítica da literatura para identificar conceitos e relações-chave, seguida da construção de modelos conceptuais detalhados para cada disciplina e as suas interações com a GenAI. A framework GAKMF está estruturada em cinco níveis interdependentes: *Organization Strategic Definition, Data and Ethical Preparation, GenAI System in a Sociotechnical Context, Knowledge Management Processes Enhanced by GenAI, and Organizational Expected Results*.

A construção e avaliação inicial da framework, informadas pela validação de especialistas através de um *focus group*, sublinham a sua relevância, rigor e aplicabilidade para investigadores e profissionais. Conclui-se que a GAKMF fornece uma lente estruturada e interdisciplinar para as organizações integrarem estratégica e eticamente a GenAI, promovendo um melhor desempenho, inovação acelerada e capacitação da força de trabalho centrada no ser humano. Esta análise tornou-se particularmente relevante, pois aborda a atual falta de representações conceptuais integradas para o papel da GenAI em ambientes de conhecimento complexos. Finalmente, este trabalho oferece insights fundamentais para o futuro design de estratégias de implementação responsável da GenAI, enfatizando a contínua interação entre os avanços tecnológicos e os fatores humano-organizacionais.

Palavras-chave: Inteligência Artificial Generativa (GenAI), Gestão do Conhecimento (GC), Gestão da Informação (GI), Gestão de Dados (GD), Governança de Dados (GovD), Design Science Research (DSR), Sistemas Sociotécnicos (STS).

Abstract

The rapid emergence of Generative Artificial Intelligence (GenAI) signifies a profound paradigm shift in how organizations manage, create, disseminate, and apply knowledge. A brief review of the contemporary literature reveals that while GenAI offers significant opportunities to enhance knowledge management (KM) processes through its capabilities in content generation, cognitive task automation, and complex data processing, its effective integration within organizational contexts remains a critical challenge. This is largely due to an underdeveloped understanding of GenAI's interdependencies with foundational disciplines such as Information Management (IM), Data Management (DM), and Data Governance (DG), which are paramount for ensuring data quality, operational optimization, and strategic alignment. Furthermore, a notable gap exists in the academic discourse regarding a comprehensive, sociotechnical informed framework that addresses the human, organizational, and ethical dimensions of GenAI deployment in knowledge-intensive environments.

Recognizing this critical need, this dissertation adopts a Design Science Research (DSR) paradigm to develop a conceptual framework: the Generative AI-Enhanced Knowledge Management Framework (GAKMF). This framework captures the multifaceted impact of GenAI on core KM processes — specifically, knowledge creation, storage and retrieval, transfer and sharing, and application — while rigorously situating this transformation within the interconnected domains of IM, DM, and DG. The research involved a critical literature review to identify key concepts and relationships, followed by the construction of detailed conceptual models for each discipline and their interactions with GenAI. The resulting GAKMF is structured across five interdependent levels: Organization Strategic Definition, Data and Ethical Preparation, GenAI System in a Sociotechnical Context, Knowledge Management Processes Enhanced by GenAI, and Organizational Expected Results.

The framework's construction and initial evaluation, informed by expert validation through a focus group, underscore its relevance, rigor, and applicability for both researchers and practitioners. It is concluded that the GAKMF provides a structured, interdisciplinary lens for organizations to strategically and ethically integrate GenAI, fostering improved performance, accelerated innovation, and human-centric workforce empowerment. This analysis has become particularly relevant as it addresses the current lack of integrated conceptual representations for GenAI's role within complex knowledge environments. Finally, this work offers foundational insights for the future design of responsible GenAI implementation strategies, emphasizing the continuous connection between technological advancements and human-organizational factors.

Keywords: Generative Artificial Intelligence (GenAI), Knowledge Management (KM), Information Management (IM), Data Management (DM), Data Governance (DG), Design Science Research (DSR), Sociotechnical Systems (STS).

United Nations Sustainable Development Goals (SGD)

UN Sustainable Development Goals

Identification of Relevant SDGs

This dissertation primarily contributes to the following United Nations Sustainable Development Goals (SDGs):

- **Goal 9 – Industry, Innovation and Infrastructure**
- **Goal 8 – Decent Work and Economic Growth**
- **Goal 4 – Quality Education**
- **Goal 12 – Responsible Consumption and Production**

Specific Targets

- **SDG 9, Target 9.5**: Enhance scientific research, upgrade the technological capabilities of industrial sectors, and encourage innovation.
- **SDG 8, Target 8.2**: Achieve higher levels of economic productivity through diversification, technological upgrading, and innovation.
- **SDG 4, Target 4.4**: Increase the number of youth and adults who have relevant skills, including technical and vocational skills, for employment, decent jobs, and entrepreneurship.
- **SDG 12, Target 12.6**: Encourage companies, especially large and transnational companies, to adopt sustainable practices and integrate sustainability information into their reporting cycle.

Contribution

This research introduces the *Generative AI-Enhanced Knowledge Management Framework (GAKMF)*, designed to guide practitioners, researchers, and organizations in the strategic and ethical integration of Generative AI (GenAI) into knowledge management processes, including the interaction between foundational disciplines such as Information Management (IM), Data Management (DM), and Data Governance (DG). The framework supports responsible innovation by incorporating sociotechnical, ethical, and organizational dimensions.

- **SDG 9 (Innovation and Infrastructure)**: GAKMF supports innovation in knowledge-intensive and industrial settings, particularly manufacturing, by enhancing knowledge creation, storage, retrieval, and application. It promotes adaptive systems and AI-driven process optimization.
- **SDG 8 (Decent Work and Economic Growth)**: By automating routine cognitive tasks and augmenting human decision-making, the framework fosters improved work quality, productivity, and workforce empowerment through upskilling and reskilling.
- **SDG 4 (Quality Education)**: The framework enhances personalized and contextualized learning for workers, enabling continuous education and development through GenAI systems.
- **SDG 12 (Responsible Consumption and Production)**: Through efficient data use and knowledge sharing, the framework contributes to sustainable organizational practices by reducing redundancy and supporting environmentally conscious innovation.

Performance Indicators and Metrics

SDG	**Goal**	**Contribution**	**Performance Indicators and Metrics**
9	Innovation and Infrastructure	Framework for AI-enhanced KM in manufacturing and other sectors	Number of AI-integrated KM systems; process innovation rate; decision accuracy with GenAI
8	Decent Work and Economic Growth	Augmentation of worker roles; reduction of repetitive tasks	Productivity per knowledge worker; adoption rate of GenAI in organizational settings
4	Quality Education	Personalized training and skill development using GenAI	Number of employees using GenAI-supported learning; efficiency of knowledge transfer
12	Responsible Consumption and Production	Sustainable use of data and knowledge assets	Reduction in task duplication; improvements in retrieval accuracy and efficiency

Table 1: Mapping of the dissertation's contributions to the UN SDGs

Acknowledgements

As author Joan Didion observed in "Goodbye to All That": "*It is easy to see the beginnings of things, and harder to see the ends*".

The completion of this journey, then, feels less like a sudden moment of arrival and more like a quiet cessation of a sustained effort. Looking back, as time rapidly escaped from between my fingers, the path was intense but, above all, a learning and invigorating experience, from which I am utterly grateful. If the end was indeed difficult to discern, its eventual realization was grounded entirely on the support of those who remained, consistent and often unseen, through its duration. For them, these acknowledgments are intended to sustain the test of time. As follows:

To my teacher and advisor, António Lucas Soares, who accompanied me through the whole process with patience, motivation and trust, leading me to openly and freely achieve my goals even when I presented obstacles. For all the support to explore and grow as a researcher, for teaching me best practices, and for broadening my scientific horizons.

To my supervisor, Henrique Diogo Silva, for, above all, being my friend, and for always being present when I most needed, helping me at all times — day and night —, for me to achieve the best results; for always listening to my doubts, thoughts, ideas, helping to refine and advance them, while also contributing to my growth as a researcher. Without him, I would not be able to finish this dissertation and other scientific achievements during this time.

To the INESC Porto, specifically CESE, for this opportunity to develop my dissertation within an incredible, supportive, and dynamic environment that cultivated in me the passion for research and to find friendship where science is happening. For all the memories, smiles, and laughter, I will be forever grateful, holding those dear memories close.

To all my friends and colleagues from CESE, specifically to Filipa, who was always an essential piece for my motivation, for always believing in me and offering advice at all times, for the help, caring and motivational words when I most needed; to Ana, for being an attentive listener, for being a company and a friend; to Miguel, Carolina, Catarina, Grasiela, Piqueiro, Romão, Miguel S., Pedro, for all the friendship and entertaining moments during my time at CESE; without them, this time would have been incredibly difficult.

To my teachers, colleagues, and friends from these past two years of my master's degree: your dedicated helpfulness and attentive support were truly invaluable, making this challenging journey a profoundly enriching experience.

To my cousin and goddaughter, Clarinha, who always motivated me to keep going, to endure all the uncomfortable and unmotivated moments, for always reminding me that I was suitable and able to accomplish my desired goals.

To my family, for all the unwavering and attentive support during the most stressful and tormented times, offering me all the help I needed to write and be fully committed to this personal and academic achievement.

To my dear friends, who walked by my side all these years and wholly endorsed my decisions, accompanying me throughout the whole dissertation passage with a smile, a necessary distraction, and positive words.

To all of you, thank you for everything, for letting me see the end of this journey in the best way possible.

Rosalina Silva

Aos meus pais.

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List of Acronyms

AI	Artificial Intelligence
DIKW	Data-Information-Knowledge-Wisdom
DM	Data Management
DSR	Design Science Research
DSRM	Design Science Research Methodology
DG	Data Governance
GenAI	Generative Artificial Intelligence
IM	Information Management
IT	Information Technology
i4.0	Industry 4.0
i5.0	Industry 5.0
KM	Knowledge Management
KMS	Knowledge Management Systems
NPL	Natural Language Processing
SECI	Socialization, Externalization, Combination, and Internalization
STS	Sociotechnical Systems

Chapter 1

Introduction

The rapid advancement of disruptive technologies associated with Industry 4.0 is significantly transforming organizational knowledge management (KM) processes. Among these advancements, Generative Artificial Intelligence (GenAI) has emerged as particularly influential technology due to its potential to automate knowledge work, support decision-making, and reshape how knowledge is created, stored and retrieved, transferred and shared, and applied (Alavi; D. Leidner, et al., 2024; Khan et al., 2024; Kaczorowska-Spychalska et al., 2024; Sumbal; Amber, 2024). As organizations increasingly deal with vast amounts of data and information with various degrees of complexity and quality, they face significant challenges in accompanying such evolution (Attard et al., 2018). It seems that information overload makes workers struggle with the "analysis, integration, dissemination, and storage" of their assets, opening a window for new technologies to effectively collaborate in these activities and possibly extract value from it (Leoni et al., 2024; Kaczorowska-Spychalska et al., 2024).

Organizations have long recognized knowledge as a critical asset to enhance products and services, drive innovation, and guarantee competitive advantage. Consequently, KM has emerged as a necessary approach to leverage this organizational knowledge (Alavi; D. E. Leidner, 2001; Alavi; D. Leidner, et al., 2024). Knowledge, distinct from data or information, is personalized, residing uniquely in individuals' minds and tied to their inherent capabilities, specific characteristics, experiences, beliefs, and educational backgrounds (Davenport; Prusak, 1998; Ikujiro Nonaka; Takeuchi, 1995; Alavi; D. E. Leidner, 2001). Therefore, knowledge management is a set of processes and practices, embedded in individuals and groups, that are dynamic and seek to capture, distribute, and use that knowledge effectively. Considering the activities of KM to improve organizational performance, GenAI presents an opportunity to redefine them completely (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024).

As a result, GenAI unfolds as a technology capable of transforming knowledge and information management within organizations through its unique ability to automate repetitive daily tasks, produce, and personalize new insights and learning (Kaczorowska-Spychalska et al., 2024; Korzynski et al., 2023; Alavi; D. Leidner, et al., 2024). Humans have cognitive limitations in information processing, memory and recall, which, in contrast, can be augmented by the capability of

GenAI tools that offer unlimited cognitive support, and act like an active knowledge co-creator due to its ability to process vast amounts of data and information through natural language(Korzynski et al., 2023; Alavi; D. Leidner, et al., 2024). For instance, GenAI has the potential to significantly enhance knowledge creation by combining, categorizing, and summarizing explicit knowledge, generating relevant insights from vast datasets, and facilitating the codification of tacit knowledge into explicit forms. Additionally, it supports the management of both structured and unstructured data, offers personalized and context-aware recommendations for workers of different expertise levels, and delivers rapid, natural-language responses during urgent decision-making processes (Alavi; D. Leidner, et al., 2024; Jarrahi et al., 2023; Kaczorowska-Spychalska et al., 2024; Benbya; Deakin University, et al., 2024). Collectively, these are a few of some of the tasks that GenAI can assist workers and, consequently, augment efficiency and productivity of organizational processes.

These changes hold particular significance for the manufacturing industry, where production environments are increasingly knowledge-intensive and reliant on data-driven decision-making. In manufacturing contexts, GenAI introduces promising applications ranging from design optimization and predictive maintenance to quality control and operator guidance, all of which depend on the creation, transfer, and application of organizational knowledge (M. Ghobakhloo et al., 2024). As manufacturing evolves toward the human-centric and sustainable principles of Industry 5.0, integrating GenAI into industrial KM processes requires not only technological readiness but also a nuanced understanding of the human-machine interaction involved (Aromaa et al., 2025).

Yet, despite its transformative potential, adopting GenAI within KM processes involves considerable risks and ethical challenges. Thus, it is paramount to advance research that can investigate the potential impacts on organizational routines and individual workers, fostering collaborative environments where humans actively control technological outputs, mitigating ethical and quality-related challenges associated with this technology (Kaczorowska-Spychalska et al., 2024; Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024; Benbya; Davenport, et al., 2020).

This dissertation seeks to explore the intersection between these complex forces (IM, KM, DM, DG), focusing on the impact of GenAI on organizational knowledge management (KM) processes. It examines how GenAI influences knowledge creation, storage and retrieval, transfer and sharing, and application across organizational knowledge-intensive contexts, explicitly incorporating insights from the manufacturing industry. By adopting a sociotechnical perspective, this research aims to provide a structured conceptual framework for organizations to strategically and ethically integrate GenAI into their information and knowledge management environments, ultimately enhancing performance, learning capacity, and innovation potential.

1.1 Context and Motivation

Recent advancements in Artificial Intelligence (AI), particularly the emergence of generative AI, signal the beginning of a new era in organizational knowledge management. This transformation is not solely technological but also profoundly social, reshaping human interactions with information and knowledge in complex and significant ways. GenAI's ability to automate and augment processes such as knowledge creation, transfer, and retrieval, introduces levels of efficiency and scalability previously unattainable (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024).

While considerable progress has been made in understanding the technical capabilities of GenAI, there remains a notable gap in the literature concerning its integration from a sociotechnical perspective. In particular, few studies thoroughly explore how GenAI affects knowledge management processes when social, organizational, and human factors are taken into account (Kaczorowska-Spychalska et al., 2024; Jarrahi et al., 2023; Leoni et al., 2024; Alavi; D. Leidner, et al., 2024).

Moreover, this research is fueled by my profound interest in contributing to the innovation of generative AI technologies within information and knowledge management field as these tools hold the potential to empower workers, enhance productivity, and shape how information and knowledge is managed. Given the rapid evolution of this technology, understanding its benefits, challenges, and risks with the ongoing transformation towards human-centered goals, where technology augments human skills, improves job satisfaction, and enables more efficient workflows (Metcalf, 2024; M. Ghobakhloo et al., 2024).

1.2 Problem Description

The emergence of Generative AI tools contributes to a revolutionary transformation in organizational contexts, offering knowledge workers new ways to manage and utilize information within knowledge-intensive environments (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024). Organizations today face a dual challenge: dealing with increasing volumes of data and information and the need to effectively implement new technologies that can potentially improve knowledge management processes as a way to enhance decision-making. Such information abundance can overwhelm human cognitive capabilities, hindering rapid and effective responses to organizational goals.

Knowledge is essential for workers to achieve their desired goals. It forms the foundation for creativity, positively contributing to a positive and effective action across all business processes (Alavi; D. Leidner, et al., 2024). All organizations comprise unique individuals, owners of knowledge that should be stored, shared and applied. When workers of diverse expertise share knowledge, the organization remains dynamic and receptive to innovation. As technologies emerging from Industry 4.0 transform all organizational aspects, researchers are confronted with powerful questions: What if there is a way to ameliorate knowledge management processes that can directly and automatically impact how information and knowledge is created, stored, disseminated, and applied? What if knowledge workers can be favorably impacted by emergent technologies, enhancing their work routines? How can humans collaborate with the adoption of technologies like Generative AI, contributing to a productive balance between them? In what ways can the information and knowledge management field evolve to accommodate this new paradigm shift?

GenAI appears as a promising technology given its ability to generate text, image, video, code, sound, and other content through access to vast datasets (Brynjolfsson et al., 2023; Kaczorowska-Spychalska et al., 2024; Alavi; D. Leidner, et al., 2024; Woodruff et al., 2024). With its extraordinary capacity and expansive cognitive capabilities, GenAI holds significant potential for automating daily routine tasks and improving the processes of creating, accessing, and utilizing information, and knowledge for decision-making. As knowledge work consists of structured and unstructured tasks, the idea that GenAI can be helpful for users to automate some structured and repetitive tasks while having the opportunity to focus on unstructured tasks that require more human cognitive skills is extremely optimistic. By using natural language processing technology, GenAI offers workers the possibility of human-like conversation, facilitating the comprehension and codification of knowledge, personalized learning and guidance through business processes (Kaczorowska-Spychalska et al., 2024; Alavi; D. Leidner, et al., 2024; Sumbal; Amber, 2024).

Across all knowledge management processes, the innovative potential of this technology is clear, "with the potential to shift the balance from mostly human-generated content to AI-generated insights" (Alavi; D. Leidner, et al., 2024). Concurrently, researchers must clarify the meaning of "mostly human-generated content", distinguishing between human workers' roles and those of GenAI. It is essential to consolidate concepts from fields such as information and knowledge management to fully understand their roles when interacting with technologies like GenAI. Research must consider the best practices and how to mitigate risks that pose a severe threat for workers, ethical considerations and process efficiency. Hence, collaboration between humans and AI should be a primary principle guiding this technological advancement.

Addressing the potential contributions of Generative AI technology in the organization environment presents a paradigm shift, where it is possible to address possible benefits that GenAI can have in organizational settings, specifically in knowledge management processes. Therefore, the contributions and implications of GenAI in organizational environments represents a critical research priority. This dissertation explores how GenAI can be strategically integrated into knowledge management by examining its impacts on knowledge creation, storage and retrieval, transfer and sharing, and application. It also investigates how foundational disciplines — such as information management (IM), data management (DM), and data governance (DG) — enable or constrain this integration, particularly in data-intensive and innovation-driven environments such as organizations and manufacturing. In doing so, this study aims to respond to a pressing gap in the literature: the need for structured, interdisciplinary, and sociotechnically informed frameworks to guide the ethical and effective use of GenAI in organizational knowledge practices.

Considering the current research gaps regarding tools like Generative AI in the information and knowledge management field, the research questions that guiding this dissertation are:

RQ1: What is the impact of Generative AI on Knowledge Management processes within organizational settings?

RQ2: What are the key sociotechnical, informational, and ethical aspects that influence the effective application of Generative AI in Knowledge Management?

1.3 Objectives and Expected Results

The primary objective of this dissertation is to explore, through a theoretical and conceptual lens, the Generative AI potential to impact Knowledge Management (KM) within organizational settings, considering the possibility of adding value to its processes. Furthermore, this research aims to address key questions related to the implementation of Generative AI and its influence in the information and knowledge management field.

Specific objectives include:

- Contribute to the state-of-art of KM by characterizing the interaction between GenAI and KM processes (creation, storage and retrieval, transfer and sharing, and application).
- Investigate the domain and interdependencies between GenAI and foundational disciplines such as Information Management (IM), Data Management (DM), and Data Governance (DG).
- Create a conceptual framework that supports the strategic and ethical implementation of GenAI in an organizational KM context.

By expanding the knowledge about these technological advancements through this dissertation, the expected results intend to contribute to the innovation in the information and knowledge management field, since the emergence of Generative AI tools is catching organizations' attention by following the idea that it can potentially impact how knowledge workers achieve their goals in more rapid and efficient ways. In addition, researchers and organizations can benefit from insights into how they can effectively implement generative AI tools to enhance knowledge creation, storage and retrieval, transfer, and application processes by ensuring that these technologies augment and enhance, rather than automate, human expertise and skills.

In a world where data, information, and knowledge are essential assets for organizational success, contributing to current scientific research that consolidates the relationships between these disciplines and GenAI opens another door for innovation, creating new possibilities for organizations to achieve improved outcomes.

1.4 Dissertation Structure

This dissertation is structured in the following chapters:

- **Chapter 1** - Introduction

Establishes the context and motivation for the study, formulates the research problem and questions, and outlines the objectives and expected contributions of the research. It also introduces the relevance of GenAI within the broader landscape of knowledge and information management.

- **Chapter 2** - Literature Review

Presents a narrative and state-of-the-art review of relevant literature concerning knowledge management, information management, data management, data governance, and Generative AI. It outlines key theoretical perspectives, conceptual distinctions, and insights that inform and supports the proposed framework.

- **Chapter 3** - The Conceptual Relation: IM, KM, DM, DG and GenAI

Articulates the interconnections between the core disciplines, Information Management (IM), Knowledge Management (KM), Data Management (DM), and Data Governance (DG), in the context of GenAI integration. This chapter introduces conceptual representations of each domain to guide the subsequent development of the framework.

- **Chapter 4** - Methodology

Details the methodological approach based on Design Science Research (DSR). It explains the rationale for adopting DSR, the use of conceptual modeling, and the incorporation of sociotechnical systems theory as an interpretive lens.

- **Chapter 5** - Demonstration and Analysis of the Generative AI-Enhanced Knowledge Management Framework (GAKMF)

Presents the developed conceptual framework (GAKMF) as the primary artifact of the study. This chapter discusses its structural components, theoretical foundations, and practical relevance, integrating insights from the literature. Additionally, the results of the focus group are represented along with the final results of the first iteration.

- **Chapter 6** - Conclusions and Future Work

Summarizes the study's key contributions, acknowledges its limitations, and outlines potential directions for future research, particularly in advancing the artifact through a more advanced research.

Chapter 2

Literature Review

2.1 Introduction

This chapter provides a literature review of the expected investigation being developed about the impact of generative AI technology on knowledge management processes within organizational settings. As a personal choice, joining a narrative and state-of-art literature review seems appropriate for the purpose of this dissertation. The decision of utilizing a narrative literature review, although its common presence in several over-the-years studies, is shaped to expose the course of the knowledge management discipline, covering the initial conceptualization of knowledge, information, and data to initiate a presentation of knowledge management's existence and significance in comparison to other disciplines such as information management. This narrative serves as a theoretical solid ground to create a bridge that presents Generative AI technology as a potential tool applicable to knowledge management processes in the organizations. Regarding the state-of-art, it starts with the display of the notion of Generative AI, following by its impact on each of the knowledge management process, offering an overview of the most relevant and recent findings on studies that present potential applications.

The development of this literature review encompassed various steps, involving the utilization of several databases and tools that helped to encounter several resources to inform and create personal scientific knowledge for the arrangement of this chapter. An exploratory research was paramount to observe and catch the general idea of the subject, including an active search for synonymous that could retrieve all the available resources about knowledge management processes and generative AI. Besides the utilization of databases such as Scopus, Web of Science, AIS eLibrary, and journals of knowledge and information management, tools like Semantic Scholar served as an exceptional and efficient option to rapidly discover relevant resources for this research. Also, in a very preliminary phase, Generative AI tools such as SciSpace, Elicit, Connected Papers, and ResearchRabbit were essential to acquire a broad view of existing resources when research questions were being refined and explored.

The overall junction of research by specific terms and the use of new and exciting GenAI tools, enabled the process of deepening knowledge to initiate the writing of the following literature review.

2.2 Knowledge Management

Knowledge exists as humans exist. The existence of knowledge starts implicitly, as humans discovered ways to transfer acquired knowledge from their experiences to effortlessly maintain skills and achievements over the years. Evolving and surviving implied the creation and transfer of knowledge to boost innovation for future generations to progress. As the world bloomed and accompanied constant advancements, particularly the rise of information technology, systematic knowledge management materialized in business-related contexts not so long ago (Wiig, 1997; Alavi; D. E. Leidner, 2001).

Nowadays, considering the emergence of new Industry 4.0 technologies, particularly Generative AI, a new perspective on how to improve knowledge management processes is being considered as a promising revolution (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024; Jarrahi et al., 2023; Kaczorowska-Spychalska et al., 2024; Korzynski et al., 2023; Leoni et al., 2024; Sumbal; Amber, 2024). The attention for these technologies grew, making organizations observant and immersed in how to incorporate these technologies capabilities into their processes. As Payne et al., 2020 claims, the field of AI is rapidly evolving and it seems like a new era is entering, causing confusion about the concepts being used. The lack of differentiation of the concepts from the information and knowledge management field overshadows the importance and potential of these technologies in the knowledge work. For this reason, an opportunity to conceptually review the relationship between data, information, and knowledge and its related processes needs to be considered. Traditional information management has focused on collecting, storing, and disseminating data and information. However, the recent emergence of AI and GenAI is shifting the focus towards managing knowledge, which is seen as more complex and valuable (Detlor, 2010; Edgar et al., 2023). Regardless of how recent Generative AI is, understanding how this technology interacts with "existing knowledge structures, networks, and routines is pivotal to ascertain its impact on organizational learning, innovation, and competitiveness" (Alavi; D. Leidner, et al., 2024).

2.2.1 Data, Information and Knowledge

To mention the importance of knowledge management for organizations, it is crucial to expose the discussion around concepts concerning the process of knowledge evolution — data, information, and knowledge. In the early literature, there is a dynamic discussion about the clarification and relation between these concepts to comprehend how knowledge is defined and produced (Grover et al., 2001; Alavi; D. E. Leidner, 2001; Fahey et al., 1998; Blair, 2002; Ikujiro Nonaka, 1994; Davenport; Prusak, 1998). According to Fahey et al., 1998, having a critical view of the distinction between each concept values the necessity for knowledge management to exist within organizations. The question of knowledge as an organizational asset and knowledge management as consequentially essential, is linked to the focus on the differentiation between data/information and knowledge management, as the information-centered approach emphasizes the capture, store, retrieve, and transmit of these objects at all times (Fahey et al., 1998). Data and information sustain all organizational processes — flourishing every and anywhere — hence, the management of these elements is crucial for the enhancement and success of the organizations. However, knowledge behaves differently, necessitating a different approach to be managed (Fahey et al., 1998). A prevalent problem for managers in organizations is the lack of understanding of the difference between information and knowledge. Hence, doubts about the management of something that is not believable or understood spawns (Payne et al., 2020; Liebowitz, 2001). It seems like an organizational theory to demonstrate the relevance of managing knowledge is lacking, one that interests organizations to give the intended value (Taherdoost et al., 2023).

The traditional hierarchical view of data, information, and knowledge demonstrated by multiple authors, envisions data as raw, unorganized numbers and facts, information as processed and structured data for a specific context and purpose and, lastly, knowledge as authenticated and personalized information (Alavi; D. E. Leidner, 2001; Blair, 2002; Vance, 1997). Contrary to data and information, knowledge does not exist by itself, it unfolds out of the individual's mind (Payne et al., 2020; Beesley et al., 2008); it involves a set of unique characteristics, where ideal conditions propose the possibility for the individual to process information and create knowledge (Alavi; D. E. Leidner, 2001; Fahey et al., 1998). Obtaining data and information is not a sufficient combination for knowledge to emerge, but the individual's experience, beliefs, education, observations, and ideas, all contributors to the creation of knowledge (Ikujiro Nonaka, 1994; Fahey et al., 1998; Blair, 2002; Grover et al., 2001; Alavi; D. E. Leidner, 2001). A way to distinguish information from knowledge is the idea that humans store and process information and, eventually, transform into personalized information, which is, essentially, knowledge (Alavi; D. E. Leidner, 2001). Oppositely, Tuomi, 1999 argues the hierarchical view defended by other authors is actually inverse. Knowledge exists before data and information as humans personalize information and, therefore, data to achieve and determine context and goal — it is the knowledge that humans hold that chooses the path of data and information (Alavi; D. E. Leidner, 2001).

The authors Payne et al., 2020 argue about the confusion across the knowledge and information management field, referring that one thing that truly differentiates knowledge and information is people. Knowledge doesn't exist without people, while information, once created, is out there to be used as an input to create knowledge. It is the intangible nature against the tangible form that information and data are characterized for. However, confusion about this relationship continues with respect to advancements in AI and machine learning. As these technologies are capable of generating content, author Payne et al., 2020 questions the use of the concepts: what should we call the outcome of the machine? Is it considered knowledge or information? The author claims that machine learning doesn't generate human knowledge, instead, it generates information that is considered "artificial knowledge". That realization comes from the logic mentioned above, as content generated by the machine still needs to be analyzed and understood by people to be considered human knowledge.

The two views of knowledge mentioned above, hierarchical and inverse, can be connected as

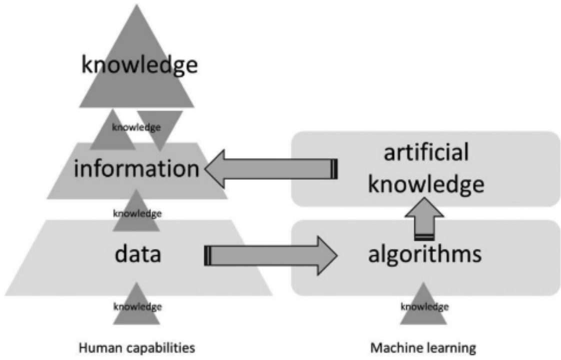

Figure 2.1: Data, information and knowledge: human capabilities and machine learning (Payne et al., 2020)

knowledge exists after data and information processing and, at the same time, the understanding of information to be applied in actions and decisions is based on existing knowledge. There are many different perspectives on knowledge, authors that understand the necessity to describe each asset, leading to the explanation of why knowledge management is paramount within organizations (Alavi; D. E. Leidner, 2001). As organizations are equipped with diverse people with specific characteristics, ranging from expertise to beliefs, unique knowledge will always be created and applied to business processes.

2.2.1.1 Two Knowledge Dimensions: Tacit and Explicit

The author Ikujiro Nonaka, 1994, adopts the view of philosopher Polanyi, 1958 of the two dimensions of knowledge — tacit and explicit —, and applies them in the business environment (Alavi; D. E. Leidner, 2001; Ikujiro Nonaka, 1994; Ikujiro Nonaka; Takeuchi, 1995; Grover et al., 2001; Tuomi, 1999). Accordingly, tacit knowledge is deeply rooted in action, experience, and involvement in a specific context (Ikujiro Nonaka, 1994; Alavi; D. E. Leidner, 2001). It is highly personal, hard to codify, formalize, and communicate (Nonaka et al., 2000; Grover et al., 2001); it is often subconscious and implicit as individuals might not be aware that they hold knowledge about a certain task and context, they just know how to naturally perform it (McInerney, 2002; Liebowitz, 2001). In contrast, explicit knowledge is easily "articulated, codified, documented, and communicated in a symbolic form and natural language (Alavi; D. E. Leidner, 2001; Ikujiro Nonaka, 1994; McInerney, 2002; Liebowitz, 2001; Grant, 1996). It is often referred to as "knowing that" and can be transmitted through documentation, such as manuals, reports, or databases (McInerney, 2002).

Although its intangible nature, tacit knowledge is a crucial asset that improves competitive advantage, innovation, and creativity (Kebede, 2010; Sumbal; Amber, et al., 2024). It is incredibly difficult to capture as it is very subjective and personal, making it a type of knowledge that needs to be acquired through experience and transferred through observation, imitation and practice (McInerney, 2002; Ikujiro Nonaka, 1994). This difficulty in capturing and codifying tacit knowledge is one challenge that organizations face and are willing to encounter new solutions to improve it.

2.2.2 The Notion of Knowledge Management

Having these perspectives on data, information, and knowledge builds up a bridge to discern the imperative necessity of knowledge management within organizations (Alavi; D. E. Leidner, 2001). The world changed its course, from relying on restricted resources to excel in operational tasks, to produce better products, to ultimately being an advanced "knowledge society" focused on turning products and services more competitive and valuable by human knowledge. From the information revolution to the knowledge revolution, knowledge and other intellectual assets were vital to best achieve business goals as customers request more innovative and specific products (Wiig, 1997).

As time and technology advanced, organizations began to be viewed as places where knowledge resides and where the interaction between systems and culture is crucial for knowledge to be discovered, shared, and used. To achieve this, many organizations have implemented structured approaches to identify, capture, and store this knowledge in organized systems. These systems facilitate knowledge access and transfer throughout the organization, ensuring that knowledge is applied effectively in different departments and processes (Alavi; D. Leidner, et al., 2024).

Knowledge management has become an essential component of digital transformation initiatives, especially for organizations aiming to achieve a competitive advantage in the changing environment of Industry 4.0 (Kaczorowska-Spychalska et al., 2024). According to Alavi; D. E. Leidner, 2001, knowledge management involves the process of creation, storage, retrieval, transfer and application of knowledge to improve organizational performance.

The question that interferes with current knowledge management research is how the emerging technologies such as Generative AI can reshape traditional knowledge management practices, since there is a huge versatility of this technology capable of changing the balance of the way knowledge is created, from mostly human-generated to AI-generated knowledge (Alavi; D. Leidner, et al., 2024).

As mentioned previously, the differentiation of data, information, and knowledge is suggested as a fundamental piece to understand their role in the field of information and knowledge management and their relationship to new technologies; this discussion serves as a foundation for the presentation of similarities between these fields and Generative AI. In the knowledge management field, Knowledge Management Systems (KMSs) — defined as information technology (IT) based systems developed to manage organizational knowledge (Alavi; D. E. Leidner, 2001) —, categorize data "as basic facts, "information" as processed and contextualized data, and "knowledge as insights drawn from human experience and judgment". However, the similarity of the results of the Generative AI technology appears promising, as it is capable of compressing the information layer and creating knowledge by processing large volumes of data (Alavi; D. Leidner, et al., 2024). This immediate processing of data and information by GenAI seems like a new world of possibilities for the KM field, as both fields are concerned with transforming data and information into actionable insights and improving organizational processes (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024; Leoni et al., 2024).

2.2.3 Knowledge Management Processes

The core knowledge management processes are often presented as a cycle or series of interconnected dynamic activities rather than a linear sequence — each process influences the other. These activities involve the creation, storage/retrieval, transfer, and application of knowledge within an organization (Alavi; D. E. Leidner, 2001). This subsection provides an overview of the core knowledge management processes, establishing a foundation for discussing the impacts of Generative AI on these processes in subsequent sections.

Starting with knowledge creation, this process involves the creation of knowledge within the organization through collaborative processes and the individual's complex cognitive capabilities (Ikujiro Nonaka, 1994; Alavi; D. E. Leidner, 2001; Alavi; D. Leidner, et al., 2024). As Davenport; Prusak, 1998 claims, "all healthy organizations generate and use knowledge". It is not only about generating ideas from scratch, but also about reconfiguring and recombining existing knowledge (Alavi; D. E. Leidner, 2001).

The authors Ikujiro Nonaka; Takeuchi, 1995 integrated four modes of knowledge conversion, the so-called SECI model, through the interaction of tacit and explicit knowledge — these are the socialization, externalization, combination, and internalization modes. All these knowledge conversation modes contribute to the whole picture of knowledge creation, procedures by which individuals experience knowledge and can transform it into and out of the organization. A brief description of each mode follows:

- Socialization: Involves sharing experiences between individuals to acquire tacit knowledge (know-how). As described by Ikujiro Nonaka; Takeuchi, 1995, tacit knowledge is gained through social interactions and experience, as it is difficult for individuals to express what is in their minds.

- Externalization: Refers to the conversion of tacit knowledge into explicit concepts. This process is considered a major challenge for organizations because tacit knowledge is hard to codify, but it is also seen as the foundation for competitive advantage, innovation, and creativity (Alavi; D. E. Leidner, 2001; Kebede, 2010; Sumbal; Amber, et al., 2024).

- Combination: Aims to transform explicit knowledge by merging, categorizing, reclassifying, and synthesizing it into new explicit knowledge (Alavi; D. E. Leidner, 2001; Alavi; D. Leidner, et al., 2024).

- Internalization: Involves embodying explicit knowledge into tacit knowledge through the process of doing and learning from activities (Ikujiro Nonaka; Takeuchi, 1995).

For instance, the author C. Liu, 2024, demonstrates the promising capacity of AI to bring new opportunities for knowledge creation and innovation to organizations through the SECI model by Ikujiro Nonaka; Takeuchi, 1995. It states that knowledge creation has an enormous value for organizational competitiveness, especially the creation of tacit knowledge.

Considering the knowledge storage and retrieval process, it refers to the organization, retention, and retrieval of knowledge, often referred to organizational memory. It includes "written documentation, structured information stored in electronic databases, individual expertise, codified human knowledge stored in expert systems, documented organizational procedures, and processes and tacit knowledge acquired by individuals and networks of individuals (Alavi; D. E. Leidner, 2001). Having effective knowledge storage ensures that knowledge remains accessible and retrievable when employees need it for future use in a specific context (Alavi; D. E. Leidner, 2001). The challenges associated with this process are related to the lack of employee time to contribute with knowledge, since the organization culture might not have implemented rewards sharing insights.

The knowledge transfer or sharing process is focused on moving knowledge to where it is needed and can be applied. This is a process that involves the flow of knowledge between individuals, from individuals to explicit sources, between groups, and across the organization. Communication and information flows are key drivers of this process, and effective knowledge transfer necessitates formal and informal mechanisms such as unscheduled meetings, seminar, coffee break conversations and training sessions that promote collaborators to share knowledge between them (Alavi; D. E. Leidner, 2001).

Finally, the knowledge application process is related to the action of using knowledge to create value for the organization. The value of knowledge it is not solely about its existence, but in how it is effectively applied in a specific context. However, there are barriers associated with this process, as workers may not trust the source of knowledge or lack the time to apply it. As a result, knowledge application needs to be supported by information technology to improve knowledge accessibility, integration, and support individuals in learning and sharing new ideas.

2.3 The Notion of Generative AI

Generative Artificial Intelligence (GenAI) appears as a significant paradigm shift within the broader field of artificial intelligence, emerging as a disruptor in the digital landscape (Banh et al., 2023). Unlike traditional AI, which mainly focuses on data AI-driven tasks such as predictions, classifications, or recommendations, GenAI is designed to create new and original content such as text, images, audios, videos, and codes similar to the outputs of human intelligence by learning patterns from data (Banh et al., 2023; Akhtar et al., 2024; Brynjolfsson et al., 2023; Formanek, 2024; Mariani et al., 2024; Sabherwal et al., 2024; Vujović, 2024; Ma et al., 2024; Kaczorowska-Spychalska et al., 2024). The impact of this technology offers a promising landscape for the business field, which is rapidly changing and adapting to the possibilities of shaping business processes and how decisions are made — creating new products, services, and automate certain tasks in the daily routine of the workers. A progressive transformation is developing, as the power of Generative AI brings the potential to not only analyze data, but creating new information from existing data sets (Kaczorowska-Spychalska et al., 2024). However, as the technology is rapidly transforming and

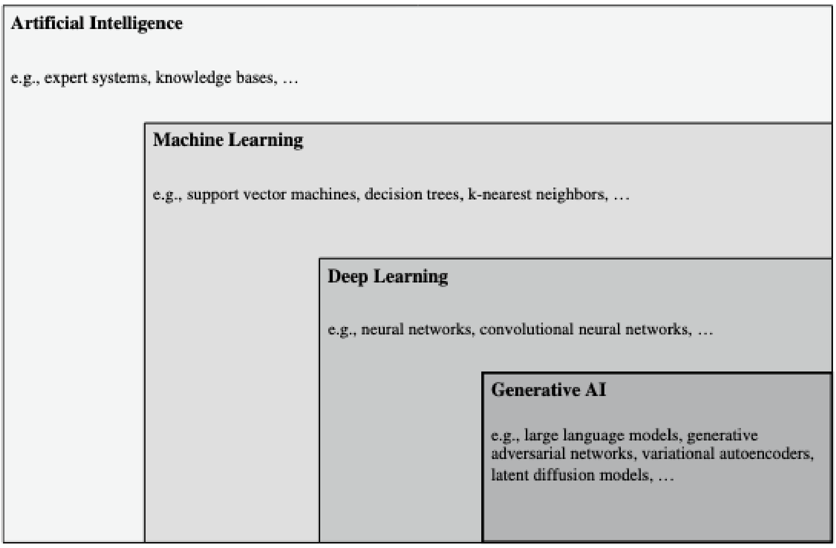

Figure 2.2: Generative AI and other AI concepts (Banh et al., 2023)

entering a new era with Generative AI, it is paramount to differentiate concepts and distinctions between technologies (Banh et al., 2023). The core concepts within AI and its sub-fields are:

- Artificial Intelligence (AI): an umbrella term for computational algorithms that perform tasks requiring human intelligence.
- Machine Learning (ML): a subfield of AI where algorithms learn from data without explicit programming. ML algorithms are discriminative (distinguish between different classes or patterns) and focus on classification, regression, or clustering.
- Deep Learning (DL): a subset of ML using artificial neural networks to model complex data and detect patterns in vast datasets.

Understanding these differences makes the emergence of Generative AI, enabled by the progress in deep learning (DL) techniques, understandable and differentiated. There are many different types of GenAI models, but the attention has been oriented to Large Language Models (LLMs), which are neural networks designed to predict the probability that the next word will appear in a sequence (Formanek, 2024); it is unique by its ability to "learn about semantic and grammatical relationships even without explicit guidance" (Brynjolfsson et al., 2023; Radford et al., 2018). That is how Generative AI is born, with capabilities that enable automation of daily repetitive tasks, provides support in generating ideas and decision-making through natural language (Kaczorowska-Spychalska et al., 2024). For instance, the authors Alavi; D. Leidner, et al., 2024 mentions recent progress, as Generative AI has launched a significant potential to "support knowledge workers and enhance their products, services, and customer support". It also refers how big companies such as McKinsey and Company are investing in GenAI to incorporate it into their knowledge management systems as a way to "facilitate streamlined search, access, analysis, and synthesis of the firm's knowledge resources for its workforce". In addition, recent studies estimate that GenAI will possibly affect various information-intensive tasks of about 80% of all workers, with a small subset of knowledge-intensive workers having a lot of their tasks affected (Eloundou et al., 2023; Benbya; Deakin University, et al., 2024).

Taking these considerations about GenAI leads to its connection to KM, considering the similarities in their objectives. Both share a goal of knowledge enhancement, since "knowledge management focuses on the capturing, distributing, and effectively using knowledge", while GenAI presents the prospect of significantly impacting each process as it can generate insights, contribute to decision-making and lead to rapid and timely solutions (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024). Due to its vast potential, GenAI presents as a tool to enhance knowledge practices, address its challenges and ameliorate the synergy between technologies and humans in the age of Industry 4.0 (Kaczorowska-Spychalska et al., 2024). The lingering question is: In what ways can generative AI's features impact the knowledge management cycle, including its related processes?

2.3.1 Generative AI Impact on Knowledge Management Processes

Generative AI has the potential to significantly transform and impact knowledge management processes within organizations and enhance how knowledge is created, stored, shared, and applied (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024; Benbya; Deakin University, et al., 2024; Jarrahi et al., 2023; Korzynski et al., 2023; Leoni et al., 2024; Taherdoost et al., 2023; Sumbal; Amber, et al., 2024). The integration of GenAI into knowledge management is not just about automating tasks but also about fundamentally leveraging knowledge assets within an organization and improving the way workers deal with knowledge work (Benbya; Deakin University, et al., 2024). In the following subsections, a state-of-art about each knowledge management process regarding the adoption of Generative AI and its potential impacts is presented:

2.3.1.1 Knowledge Creation

In all organizations, knowledge is produced constantly by workers in concrete contexts — from tacit to explicit —, and it flows within groups and organizational objects. The human brain is extremely complex, capable of producing knowledge through collaborative and social processes among people, but, although its unique particularities, it has cognitive limitations that might be overshadowed by the introduction of artificial intelligence, especially GenAI tools. This is a constraint that affects the efficiency and speed at which knowledge can be created. (Alavi; D. Leidner, et al., 2024). The level of data and information tends to grow rapidly over the years, making humans in a difficult situation in terms of processing it (Leoni et al., 2024). In contrast, GenAI offers unlimited cognitive capabilities to process information, guiding the human worker to a better and faster decision. It offers the possibility of automatically create documents by analyzing enormous amounts of data (Seth Earley, 2023). Workers who deal with many processes-related documents that need to be read to capture relevant information can utilize GenAI to automatically extract important information from sources of different formats and types (Kaczorowska-Spychalska et al., 2024).

Furthermore, GenAI facilitates the synthesis of new knowledge by merging, categorizing, and summarizing explicit knowledge from different sources, which promotes the combination mode of knowledge creation by its ability to generate content and identify patterns (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024; Korzynski et al., 2023). For example, in the pharmaceutical and material science industry, generative AI can be used to analyze pertinent explicit resources to explore new chemical compounds or specific materials that would have taken longer for human researchers to uncover (Benbya; Deakin University, et al., 2024; J. S. Lee et al., 2023; Ni et al., 2023). The author Alavi; D. Leidner, et al., 2024 refers the workers' possibility in facilitating their learning experience during an organizational process, since GenAI is able to respond to queries with personalized information that helps them achieve their desired goals regardless of their level of expertise. These technologies represent skills that surpass human skills such as the ability to code, since they can explain workers how to code in natural language explanations, helping workers quickly apply their knowledge to the task in hand (Brynjolfsson et al., 2023; Alavi; D. Leidner, et al., 2024). This individual and personalized learning contributes to the internalization mode of knowledge conversion, as workers can use the knowledge provided by GenAI to internalize it, transforming the explicit to tacit knowledge. Yet, it can be difficult to guarantee what workers are employing upon the use of this technology (Alavi; D. Leidner, et al., 2024).

According to the study by Leoni et al., 2024, results indicate that the use of GenAI aids workers to generate new ideas and analyze data faster, having a positive impact on their customers. At the same time, the study by Kaczorowska-Spychalska et al., 2024 affirms that having access to ideas and solutions from GenAI does not make workers discharged of creative thinking, since "employees and managers must have the creativity to use these ideas and solutions in the knowledge management process". This technology is also prone to hallucinations, producing inaccurate outputs that look extremely similar to reality (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024; Seth Earley, 2023; Kaczorowska-Spychalska et al., 2024). The promising potential of GenAI to generate new content appears essential for decision-making processes, however, it is paramount to consider its limitations, as organizations are losing control of what kind of knowledge is relevant for the organization, since GenAI is trained on vast amounts of data, and without human oversight and supervision to ensure the authenticity of the produced outputs it can hinder problems to the success of processes (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024; Jarrahi et al., 2023). As Seth Earley, 2023 states, "LLMs do not automatically know your company's language, terminology, acronyms or processes", opening the discussion about the collaboration between humans and technology.

The literature also mentions the impact on the socialization mode of knowledge conversion, however, not so positively as other modes with the possibility of affecting the way workers share knowledge within the organization. For instance, socialization is crucial to share experiences, mental models, skills that are hard to articulate between collaborators, impacting innovation within processes (Sumbal; Amber, 2024). But Generative AI, by providing answers to any question and offering insights in different expertise level, can influence human interaction and shrink social networks by an over-reliance on the technology (Alavi; D. Leidner, et al., 2024; Woodruff et al., 2024; Benbya; Deakin University, et al., 2024). Also, if collaborators don't socialize with each other because they are individually learning and generating content, then the externalization of knowledge might be affected if they are not sharing it (Alavi; D. Leidner, et al., 2024).

Nevertheless, Generative AI holds immense potential as a co-creator of knowledge, augmenting human skills by boosting learning, accelerating the speed of knowledge creation, and enabling organizations to explore new routes of innovation that were previously inaccessible due to cognitive limitations of the workers as data and information grows exponentially in volume and complexity.

2.3.1.2 Knowledge Storage and Retrieval

Knowledge storage and retrieval face the possibility of improving its processes with the adoption of Generative AI, but not without new associated challenges (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024; Kaczorowska-Spychalska et al., 2024). Historically, organizations deal with knowledge that is both explicit, which is codified in documents and systems, and tacit, which is "stored within individuals, groups and organizational culture". The appearance of knowledge management systems incorporated a new way to store less structured data, but a prominent challenge was the difficulty in convincing employees to share their knowledge. For organizational and social reasons, employees were hesitant to codify their tacit into explicit knowledge due to fear of losing their uniqueness and importance and lack of time (Alavi; D. Leidner, et al., 2024). As the management of tacit knowledge constitutes a critical factor to organizational success, Sumbal; Amber, et al., 2024 it suggests that through feedback and reflection, employees can create prompts to retrieve reflections on their own experiences and receive feedback on their performance. That also leads to a kind of mentoring by these tools, as it can recommend opportunities to develop tacit knowledge shaped by each unique individual's characteristics. These tools are efficient in this codification and transformation of tacit into explicit knowledge due to their natural language processing abilities, which also leverages information retrieval, as it can understand user queries (Jarrahi et al., 2023; Benbya; Deakin University, et al., 2024). Another crucial feature of GenAI in knowledge storage and retrieval, is the ability to automatize the classification of unstructured data, "categorizing, tagging, and labeling data" to easily access and retrieve information required for a specific decision-making situation (Kaczorowska-Spychalska et al., 2024; Leoni et al., 2024; Jarrahi et al., 2023).

In terms of challenges, while GenAI provides rapid access to a vast amount of knowledge, doubts are raised about the use and proper applicability of knowledge (Alavi; D. Leidner, et al., 2024). The author Kaczorowska-Spychalska et al., 2024 also mentions the potential loss of knowledge if there is no human oversight to ensure that valuable knowledge is still preserved.

The ability of this emerging technology to automate processes, enhance accessibility, and handle diverse types of data offers significant advantages for organizations regarding knowledge storage and retrieval practices. However, challenges related to data quality, ethical considerations, and the balance between human and AI-generated content should be considered.

2.3.1.3 Knowledge Transfer and Sharing

Organizations holds knowledge that can be difficult to evaluate, having to deal with some complexities in terms of how much knowledge they hold, who needs it, and where it is available (Alavi; D. Leidner, et al., 2024). During a specific business process, relevant information is crucial for workers to achieve a better solution. The adoption of Generative AI seems encouraging, as it can recommend feedback tailored to user needs by responding to its queries, enabling knowledge sharing and personalized learning (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024). For instance, Alavi; D. Leidner, et al., 2024 demonstrates an example where GenAI can be extremely helpful in knowledge transfer by facilitating the entry of new employees by transferring knowledge indicated to their specific role and skills through interactive tutorials and simulations, helping them to integrate more easily into the organization. Additionally, employees may find easier to ask GenAI instead of communicating with older coworkers. Although these advantages represent an evolution in how knowledge transfer operates, new challenges materialize as organizations might find difficult to control what knowledge is being transferred to employees, as information can be sensitive and privileged (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024). It is important to understand the business and operational contexts to retrieve the best output of an important decision, which GenAI might struggle to master the context and complexities of a specific project.

GenAI offers powerful tools to enhance the transfer and sharing of knowledge, including the ability to personalize learning, simplify projects, and improve easier accessibility. However, organizations must carefully address the risks associated with over-reliance, loss of control, and the potential misuse of sensitive information, aiming for a balanced approach that integrates GenAI while maintaining insights from humans within the process.

2.3.1.4 Knowledge Application

Knowledge application is a key element of knowledge management since organizational processes can only add value if knowledge is properly applied (Alavi; D. Leidner, et al., 2024; Jarrahi et al., 2023). Organizations aim to enhance productivity and efficiency, leading to an increased interest in implementing GenAI tools as solutions where employees can collaborate and apply knowledge in decision-making situations (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024; Kaczorowska-Spychalska et al., 2024; Leoni et al., 2024). GenAI's ability to understand natural language creates opportunities for workers to rapidly search and access to stored knowledge, which can be crucial in certain organizational contexts. Use cases in this topic demonstrate that GenAI truly helps improve performance. As authors Alavi; D. Leidner, et al., 2024 illustrate, GenAI can support knowledge management processes when integrated into enterprise software systems such as Microsoft Teams — meetings can be automatically transcribed and summarized, aiding workers to rapidly and efficiently manage their routines and tasks. Additionally, activities such as coding can significantly benefit productivity as less experienced workers can receive guidance to write faster and with fewer errors — allowing workers of varying expertise to perform tasks at comparable levels (Alavi; D. Leidner, et al., 2024; Benbya; Deakin University, et al., 2024). Conversely, productivity can only be achieved if employees receive adequate training, do not waste too much time on irrelevant queries, and carefully curate the knowledge they apply. Unreflective guidance can lead to errors, negatively impacting the organization. To mitigate these risks, workers must understand how to leverage these technologies to augment their skills and improve their analytical skills from large data sets. It is paramount that GenAI outputs are properly analyzed and compared to human outputs to ensure well-informed decisions. If organizations address these risks effectively, GenAI will clearly support decision-making processes (Leoni et al., 2024; Kaczorowska-Spychalska et al., 2024).

However, adopting GenAI tools in knowledge application can introduce additional risks. Organizations employing GenAI-generated knowledge may face issues related to the handling of sensitive data, data leaks, and potential misuse of data against the organization's interests (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024). Organizations must therefore invest in ethical frameworks to include GenAI's transformative potential in knowledge application (Benbya; Deakin University, et al., 2024). Establishing a balanced collaboration between human workers and GenAI in knowledge management practices appears beneficial for fostering future organizational innovation and process enhancement.

2.3.2 GenAI in Manufacturing

In previous sections, the impact of Generative AI was primarily examined in relation to knowledge management processes within organizational contexts. This section expands the scope to encompass the manufacturing industry by presenting a state-of-the-art overview of how GenAI is fundamentally transforming the sector through its novel generative capabilities, which directly affect both the operational environment and the workforce.

As author (M. Ghobakhloo et al., 2024) observes, Generative AI has made some advancements in the business sectors (Prasad Agrawal, 2024), but regarding the manufacturing industry, it remains unexplored, especially in the academic world. This lack of depth in research leads to the importance of investigating GenAI in manufacturing, especially through a sociotechnical lens.

The industry is metamorphosing into a new paradigm driven by emerging technologies, which promise significant reshaping of operational processes (M. Ghobakhloo et al., 2024), workers' cognitive aspects (Aromaa et al., 2025) and collaborative dynamics (Escobar et al., 2025; Ma et al., 2024), and strategic business planning (Rajaram et al., 2024). To effectively contextualize GenAI within the manufacturing industry, it is essential to examine the transition from Industry 4.0 (i4.0) to Industry 5.0 (i5.0). Given GenAI's human-like capabilities, its integration into industrial processes requires alignment with i5.0's core principles — namely, human-centricity, sustainability, and resilience (Morteza Ghobakhloo et al., 2023; M. Ghobakhloo et al., 2024; Waschull et al., 2023; Potthoff et al., 2024). The inherent limitations of Industry 4.0, particularly its "technocentric vision" focused predominantly on enhancing productivity, efficiency, and flexibility, underscore the continued imperative to achieve these goals while simultaneously emphasizing "human-machine collaboration, customization, and adaptability in achieving sustainable and innovative manufacturing practices"(Molina, 2023; Latino, 2025). As GenAI posits new possibilities for a dual capacity of augmenting and, in some cases, automating workers, the ideals of i5.0 are paramount to integrate this advanced technology into manufacturing practices (M. Ghobakhloo et al., 2024), transforming the nature of work and organizations in a perspective that complements humans, mitigates potential disruptions, and applies sustainability ideals (Banh et al., 2023; Krakowski, 2025; Kiangala et al., 2024).

Therefore, critical questions emerge: What is the impact of GenAI on manufacturing processes and workers? How does GenAI influence information and knowledge-intensive manufacturing processes? Manufacturing processes operate in highly data-intensive environments, from smart devices and machines, which require storage, processing, and analysis of that data (De Simone et al., 2023). In addition to generating a lot of data, manufacturing processes involve a variety of types of information and knowledge that are essential for effective performance. For instance, tacit knowledge is crucial since it includes insights from human experts and operators to ensure task effectiveness and solving non-routine problems that explicit knowledge cannot directly solve; while codified knowledge, such as explicit, communicates workers on how to proceed through rules, specifications, manuals, documented procedures (C. W. Choo, 1996; Chun Wei Choo, 2002). Thus, based on GenAI's ability to generate new and original content such as text, images, audio, video, and code (Feuerriegel et al., 2024), while also being considered a general-purpose technology (GPT) capable of driving innovation, enhancing cognitive abilities, and democratizing AI adoption (Krakowski, 2025), there are positive impacts on the manufacturing industry.

Author (M. Ghobakhloo et al., 2024), explores GenAI's potentialities in manufacturing according to i5.0 values, specifically sustainability goals. The capacity to rapidly and efficiently learn from patterns and adapt to specific contexts, brings diverse possibilities from "design optimization to predictive maintenance, generative AI can possibly be leveraged to streamline operations, reduce waste and improve overall efficiency" (**castaneASSISTANTproject2023**; M. Ghobakhloo et al., 2024). How can manufacturers be more sustainable along GenAI integration? As GenAI is capable of contributing to "design iterations and process optimization", products are being selectively produced and customized by following generated insights about customers' demands, which reduces the environmental impact considering resource consumption and waste. At the same time, manufacturers reduce costs by acquiring and using only materials that are essential for production (M. Ghobakhloo et al., 2024). It all starts with data and GenAI's ability to transform it into information and knowledge.

Indeed, manufacturers deal with a lot of data, such as real-time, data-driven insights that needs to be transformed into insights and contextual and meaningful information. This transformation nourishes possibilities for creative processes and productivity enhancement. If companies are suitable to utilize available data effectively along GenAI tools, predictive abilities can also contribute to generate forecasting trends, associated challenges and needs, which are crucial in a decision-making occasion (M. Ghobakhloo et al., 2024; Doanh et al., 2023; Modgil et al., 2025; Khan et al., 2024). Generating actionable insights appears a promising and revolutionizing ability, reducing time for research and development of new products (Escobar et al., 2025). As these processes and tasks are assisted and augmented by GenAI, human workers can be freed to perform more complex and strategic tasks (Modgil et al., 2025; Sai et al., 2025a; Amankwah-Amoah et al., 2024; Krakowski, 2025). Thus, by supporting cognitive functions, humans can easily process information and acquire knowledge in a more effective and rapid way, enhancing individual and organizational learning (Alavi; D. Leidner, et al., 2024; Aromaa et al., 2025). In the context of manufacturing, it is extremely relevant that workers are receiving proper training and enhancing skills to perform industrial tasks that requires knowledge, particularly new employees (Xu et al., 2024). Generative AI can act as a personalized tutors for each operator expertise, guiding them with "suggestions on various domains such as equipments adjustments, maintenance schedules and even optimal spare parts purchases". At the same time, since it learns patterns continuously, it is able to adjust and update knowledge to current needs. This knowledge transfer task is assisted by this technology leading the company to reduce costs and resources in terms of training and upskilling operators (M. Ghobakhloo et al., 2024). In addition, (Storey, 2025) states how GenAI impacts different levels of worker's expertise in relation to GenAI assistance — novice workers are more willing to use GenAI to perform tasks, while expert workers, possessing more tacit knowledge acquired over years of experience, are more focused on evaluating the quality of the generated outputs. These progresses related to knowledge transfer, creation and application processes that are directly impacted by GenAI on workers routines and well-being — from augmenting to enhancing collaboration — aligns with human-centricity goals from i5.0 that industries yearn to accomplish. Still, there are more achievements with this technology in the manufacturing sector. For instance, quality control processes can be greatly enhanced by Generative AI. These processes are extremely rigorous and necessitate a meticulous identification of product defects. GenAI is capable of analyzing images or data from manufacturing processes, allowing manufacturers to detect defects in real-time on the production line, ensuring products meet quality standards before reaching customers. Simultaneously, through an analysis of vast data sets, it can identify patterns that might lead to a potential defect and study how an area can be improved (Doanh et al., 2023; Escobar et al., 2025). Once again, the idea that knowledge can be generated from data and help workers to understand how a product is acting before it is a problem is the basis. This capability enhances productivity, optimizes performance, and reduces waste. Author (Shafiee, 2025) states that industry experts expect that integration of GenAI tools in manufacturing can "boost productivity by 15-20% through optimization and error reduction" and also "reduce defects by 20-30%, improving customer satisfaction and reducing waste".

These are promising implementations for the manufacturing industry although, as expected, challenges and considerations need to be considered for results to be effective.

2.4 Challenges and Ethical Problems

Integrating a technology such as Generative AI within an organization seems extremely tempting considering all the possibilities and capabilities it offers. In current days, organizations are profoundly interested in adopting AI technologies or looking for information about them (Aunimo et al., 2023). Its transformative potential brings enhanced efficiency and collaboration, innovation, improved decision-making, and the creation of other forms of value across various sectors (Akbarighatar et al., 2023; Baier et al., 2025; Modgil et al., 2025; Przegalinska et al., 2025). The relationship between cognitive technologies and knowledge work is intrinsic, primarily due to these technologies' capacity to generate and transform information and knowledge. This integration is designed to enhance productivity and drive organizational success, emphasizing the critical insight that "knowledge work productivity is the key to economic success in the twenty-first century" (Davenport, 2018). Nonetheless, implementing these technologies and achieving satisfactory results isn't simple; it presents challenges ranging from technological, organizational, social, and workforce issues to ethical considerations.

It all starts with data.

Employing AI technologies, such as GenAI, presents a significant opportunity that not all companies can readily integrate into their tasks and processes. A major distinguishing factor lies in organizational size: large organizations often possess greater financial resources and more abundant data compared to small to medium-sized enterprises (Davenport, 2018). GenAI systems, in particular, are heavily dependent on both the volume and quality of data to function efficiently and to produce reliable outputs (Haridasan et al., 2024; Banh et al., 2023). Furthermore, larger companies can typically "afford to pay proprietary vendors, expensive consultants, and expensive data scientist as employees", which collectively enhance their capacity to adopt and leverage technologies like GenAI. It is about well-established processes, strategies, and resources that can greatly enhance an organization possibility to adapt and accompany digital transformation evolutions (Davenport, 2018). Thus, the most prominent consideration that establishes GenAI's implementation is data availability and quality. Since GenAI learns patterns and generates insights from vast volumes of input data, often referred to as "training data", their ability to generate reliable, accurate, and relevant content is directly tied to the quantity and quality (Akhtar et al., 2024; Haridasan et al., 2024; Kusiak, 2025; Sai et al., 2025b). Consequently, all the technology benefits and impacts that leverages people, processes, decisions, and organizations is utterly affected. Then, how can organizations handle problems related to data quality? To implement and monitor GenAI, organizations and manufacturers require data management and governance methods and strategies to cover this problem (Abraham et al., 2019; Prasad Agrawal, 2024; Akbarighatar et al., 2023; Aromaa et al., 2025; Chowdhury et al., 2022). In Chapter 4.2, an approach of Data Management (DM) and Data Governance (DG) is presented to consolidate the importance of implementing them within the context of this dissertation.

Still related to DM and DG, GenAI also poses threats to privacy and security which are hard to understand and explain due to its "black-box" nature. As data, such as personal data, is being gathered, it is important to comprehend how this data is being stored, managed, and used so that privacy is not compromised (Beatriz Andres et al., 2024). Organizations must ensure that data is "handled responsibly with explicit consent" while following ethical standards. At the same time, when gathering and organizing data that will train a GenAI model, it is paramount that its nature is diverse, free from biases, and representative (Aromaa et al., 2025; Jin et al., 2024; Kanbach et al., 2024). Why is this important? Ethical considerations act as a foundation for trust and between business and customers and stakeholders, and, not less importantly, between workers and the machine (Jin et al., 2024; Dwivedi; Hughes, et al., 2021). As author (Wei et al., 2025) argues, bias concerns "necessitate careful design and robust governance, and information management" to ensure that cognitive technologies "not only enhance organizational efficiency and decision-making but also promote social justice and equity".

Workers fear and question the future now that technologies such as Generative AI can augment and automate their work (Banh et al., 2023; Makarius et al., 2020). To align with i5.0 values, human workers must be protected to foster a synergy between humans and machines. This is crucial because humans possess irreplaceable capabilities like creativity, problem-solving, and intuition, which, despite GenAI's significant assistive capacities, provide significant and unique value to organizations (Molina, 2023; Grybauskas, 2024; Leng et al., 2022; Waschull et al., 2023; B. Andres et al., 2025). Conversely, major concerns exist regarding over-reliance, deskilling of workers, and loss of tacit and unarticulated knowledge (Krakowski, 2025; Storey, 2025; Aromaa et al., 2025). This happens because workers can become dependent on GenAI's outputs without using critical thinking to validate its accuracy and relevance. For that, organizations must ensure that workers are properly trained and informed, encouraging them to apply their creativity and judgment abilities (Krakowski, 2025). Author (Alavi; D. Leidner, et al., 2024) notes that socialization can be affected as junior workers might rely excessively on GenAI, losing the ability to effectively share knowledge and collaborate. Over-reliance can lead to knowledge and information loss and lack of socialization, risking organization to lose critical organizational knowledge. Moreover, as workers increasingly rely on GenAI's outputs for decision-making, it is fundamental to consider ethical issues regarding responsibility and accountability (Aromaa et al., 2025; Janssen, 2025). Explainability and transparency, therefore, are central to responsible AI use (Dwivedi; Hughes, et al., 2021), necessitating governance strategies to ensure that human-machine collaboration aligns with business needs.

These challenges and problems associated with developing, employing, and using GenAI within organizations provide researchers a broad landscape to explore this technology across social, technical, and organizational factors.

Chapter 3

Methodology

3.1 Introduction

This chapter outlines the methodological approach employed in conducting this dissertation. As author (Pickard, 2013) argues, "in the research hierarchy there is no doubt that a research paradigm implies a research methodology". Accordingly, the present study adopts a qualitative research design informed along with the Design Science Research (DSR) paradigm, which supports the construction of purposeful artifacts through rigorous examination and reflective iteration.

Grounded in this paradigm, the research advances through the development of conceptual representations and a framework designed to explore and facilitate the integration of Generative AI (GenAI) into organizational Knowledge Management (KM) processes — from organizational strategic definition to organizational expected results.

The study employs an extensive literature review and a critical interpretive analysis of a curated corpus, from which key concepts and relationships are identified and formalized through conceptual modeling techniques. The idea is to create conceptual models establishing relationships between different foundational disciplines interacting with GenAI - IM/GenAI/KM and DM/GenAI/DG — to construct the narrative supporting the proposed framework. Furthermore, conceptual models for each discipline separately are developed to enhance understanding and representation of each domain.

The outcome of this methodological process is the construction of a theoretical framework that synthesizes interactions among foundational disciplines, GenAI's impact within KM theory to achieve better organizational results, and incorporates a sociotechnical systems perspective. To evaluate and validate the artifact developed in this dissertation, the data collection technique of focus groups will be performed.

3.2 Research Design

The research paradigm selected for this dissertation is the Design Science Research (DSR). The decision to utilize DSR as a foundation to design this master's degree dissertation emerged from

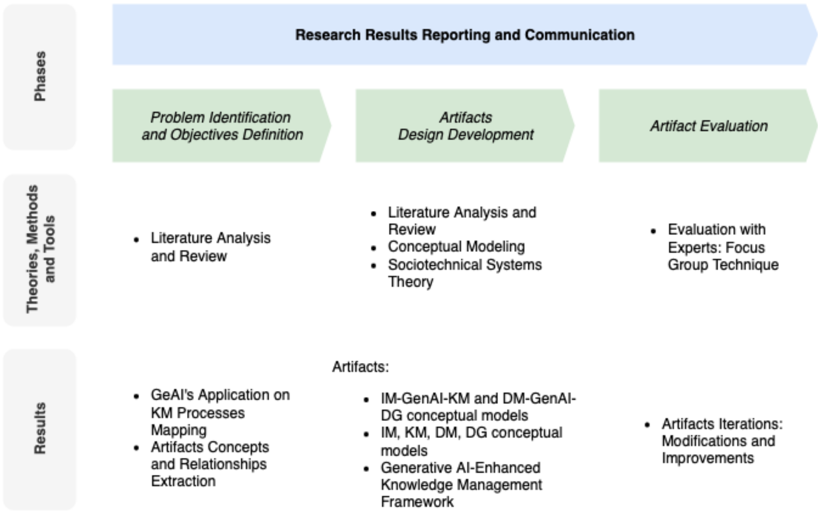

Figure 3.1: DSR Research Phases

the necessity to investigate, address, and solve a real-world problem that is intriguing organizations: the rapid advancements of AI technologies, such as Generative AI, which offer human-like capabilities that can potentially alter the course of organizational and workers processes. DSR is a well-established paradigm in Information Systems (IS) research focused on creating innovative artifacts (constructs, models, methods, or instantiations, for example) (A. R. Hevner et al., 2004) to address real-world problems and contribute to a body of knowledge (C. Hevner, 2010). Originating in the engineering field and the science of the artificial (Simon, 1996), DSR is fundamentally a problem-solving paradigm that enables researchers and practitioners to comprehend the problem and develop effective artifacts (A. R. Hevner et al., 2004).

This research aims to construct a primary and final artifact — a conceptual framework — designed to bridge theoretical insights from knowledge management (KM), information management (IM), data governance (DG), data management (DM), and GenAI, while integrating a sociotechnical systems (STS) theory in order to provide a structured lens to guide organizations to effectively adopt GenAI into KM processes. Problem identification and objective definition, based on the identification of business needs, understanding of the environment, and recognition of problems and opportunities, are achieved through an extensive literature analysis and review. As depicted in Figure 3.1, the outcomes obtained from employing the DSR research design are a structured mapping of potential GenAI applications in KM processes. Concurrently, by gathering various sources on the topics of the research, it was possible to extract the concepts and relationships that shaped the construction of the conceptual models in chapter 3. Additionally, section 3.3 provides a more detailed description of the steps that methodologically supported the creation of the conceptual models. The knowledge acquired from the reading and analysis of the curated sources provided critical thinking to further select the most relevant concepts and relationships for the context of the dissertation, in particular for the development of the framework.

In the "Artifacts Design Development" phase, methods and theories were used to provide

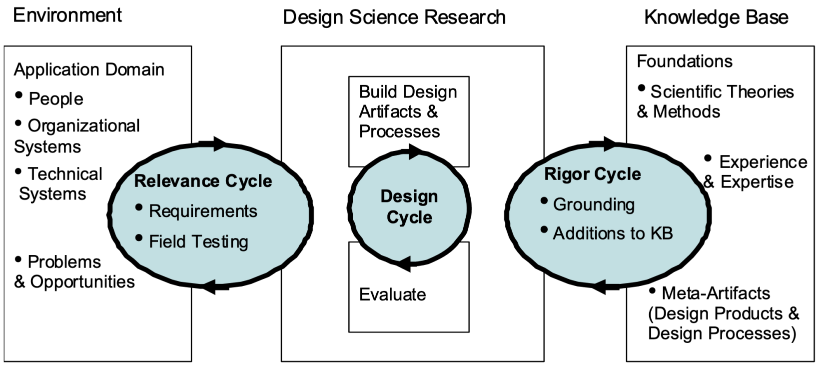

Figure 3.2: Design Science Research Cycles (A. R. Hevner, 2007)

foundational support for the creation of these artifacts. The literature analysis and review served as the primary method for constructing all artifacts, complemented by conceptual modeling methods and sociotechnical systems theory, which is integrated into the final framework. The results spared between chapter 3 and chapter 5 are conceptual modes of the relationship between IM-GenAI-KM and DM-GenAI-DG; conceptual models of each discipline to easily understand and visualize their domain, aligned with the context of the dissertation; finally, the Generative-AI enhanced knowledge management framework, where it is presented the GenAI application on KM processes with the alignment of each discipline necessary to design and adopt this technology effectively and accordingly to business needs and goals. After the artifacts are designed and developed, it is necessary to proceed with the phase "Artifact Evaluation", where a focus group is performed to offer qualitative insights about the utility, usability, and effectiveness of the resulted artifacts. By exploring the strengths and weaknesses of the conceptual models and framework, more iterations are supported for the refinement of these artifacts.

Now, to provide a clearer understanding of the key properties and processes of DSR, the next subsection presents (A. R. Hevner, 2007)'s conceptualization of the research paradigm through a complementary three-cycle model.

3.2.1 Design Cycles

The DSR research paradigm, as articulated by (A. R. Hevner, 2007), is fundamentally structured around three interconnected cycles that ensure both practical relevance and academic rigor:

- **The Relevance Cycle:**

This cycle grounds the research in real-world environments by identifying problems or opportunities and inferring requirements for the artifact. According to A. R. Hevner (2007), DSR should begin by "representing opportunities and problems in an actual application environment." After construction, the effectiveness of the artifacts is tested, and the results guide subsequent iterations if needed.

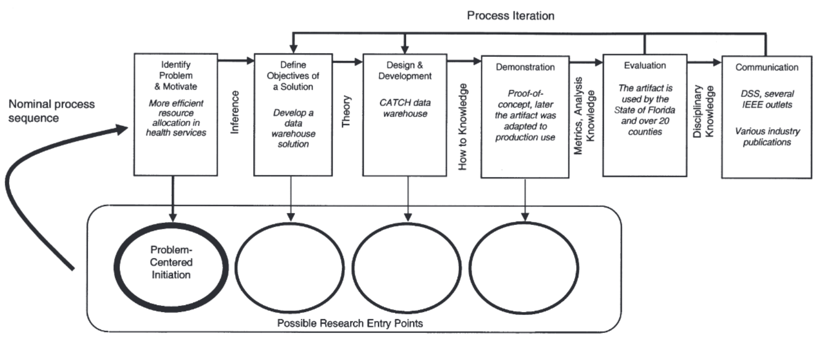

Figure 3.3: Design Science Research Methodology process model (Peffers et al., 2007)

- **The Design Cycle:**

This cycle focuses on constructing and evaluating artifacts through iterative refinement. As Simon (1996) notes, it involves generating, comparing, and adjusting design alternatives until they meet research requirements. Evaluation is essential, as the value of design science lies in the rigorous testing of artifacts (A. R. Hevner, 2007).

- **The Rigor Cycle:**

This cycle connects the research with the existing knowledge base. Researchers apply relevant theories, methods, and prior expertise to ensure innovation, rather than the routine application of known solutions (A. R. Hevner, 2007). Thus, in order to obtain the expected results, the development of the methodology followed the design of a DSRM process (Peffers et al., 2007). Various authors in the IS field contributed to the development and evolution of the process elements that constitutes the DSRM process.

According to (Peffers et al., 2007) the DS research consists of six activities, represented in the figure 3.3. They follow:

- **Problem identification and motivation:**

The DSR begins by identifying a relevant and significant problem that needs a novel solution. Organizations increasingly show interest in deploying GenAI to enhance their processes, yet a clear need exists for research and artifacts that guide proper deployment of these technologies to achieve optimal results (Ma et al., 2024; Prasad Agrawal, 2024; Duan et al., 2019; Makarius et al., 2020). Problem identification and motivation are initiated through an extensive literature review on relevant topics, which facilitates the discovery and documentation of research gaps supporting the current study. Understanding the challenges and complications organizations face in relation to Generative AI, their businesses needs and, consequently, its impact on KM processes was the first foundation for the requirements supporting the launch of this research. After analyzing various articles, knowledge was acquired to create conceptual models of the disciplines crucial for effective GenAI adoption in KM processes.

As previously mentioned, the problem identification and motivation relate to the ongoing technological evolution that motivates organizations to adopt these technologies to enhance productivity and process efficiency (Amankwah-Amoah et al., 2024; Kanbach et al., 2024; Krakowski, 2025; Prasad Agrawal, 2024). However, there are problems and challenges related to this implementation (Akbarighatar et al., 2023). Besides the technocentric view of all research pertaining this technology, organizations face problems with data accessibility, data quality, data availability (Makarius et al., 2020; Aromaa et al., 2025; Taeihagh, 2025). These problems often stem from poorly defined and misaligned business strategies and inadequate data management and governance frameworks, causing organizations to struggle with effective technology design and implementation.

- **Define the objectives for a solution:**

Objectives for the solution are derived directly from problem identification. Advancements in the literature review process reveal existing problems and potential solutions, guiding the definition of artifacts to address unfulfilled research areas. Although Generative AI is not yet widely implemented within organizations, existing studies provide preliminary insights and direction for future research. Thus, by creating conceptual models as artifacts of each discipline (KM, IM, DM, DG) and technology (GenAI), it provides a visual representation of their roles, capabilities, and relationships. Understanding the impact on how GenAI can be effectively designed and employed within organizations, informs the objectives for the creation of a solution that could be helpful for practitioners, researchers, and, eventually, organizations, helping them align GenAI implementation with business objectives and expected results. For researchers and practitioners, these models provide a foundational basis for a deeper, more informative research.

- **Design and development:**

During this activity, the artifact is designed and developed. The conceptual framework follows the (Alavi; D. E. Leidner, 2001)'s knowledge management processes framework (knowledge creation, knowledge storage and retrieval, knowledge transfer and sharing, and knowledge application) as its primary theoretical foundation, where GenAI can potentially impact (Alavi; D. Leidner, et al., 2024). Additionally, the integration of disciplines such as DM, DG, and IM, along with a sociotechnical system (STS) theory, perspective that acknowledges the continuous interplay between technical systems and social aspects (Akbarighatar et al., 2023). The creation of this conceptual framework follows the DSR cycle, which encompasses evaluation and validation for future refinements.

- **Demonstration and Evaluation:**

Artifact demonstration and evaluation are conducted through a focus group comprising social and technical systems experts, essential for assessing and refining the artifact's utility, contextual relevance, and theoretical robustness. As a data collection technique, the focus group is particularly well-suited at any stage of the research design, gathering data from various sources simultaneously. As a data collection technique, the focus group is particularly well-suited at any stage of the research design, allowing for the simultaneous gathering of diverse perspectives. In this context, the focus group is strategically employed at the final stage of data collection. This timing enables experts to confirm emerging findings (Pickard, 2013), aligning with the primary objective for the demonstration and evaluation of the artifact developed in this dissertation. However, it is important to note that an informal workshop was previously conducted to demonstrate the initial iterations of the artifact, engaging experts in the Information Science and Generative AI/technological fields. This preliminary workshop served as a valuable incentive for future iterations and guided the artifact's development based on the topics discussed.

- **Communication:**

The final DSR step involves communicating the design artifact, highlighting its utility and effectiveness to academic and practitioner communities. This master's degree dissertation will be publicly presented and subsequently published in the University of Porto repository. Additionally, a peer-reviewed research paper based on this dissertation, entitled "*Generative AI as a Catalyst for Collaborative Knowledge Management: Impacts Across Individual, Intra, and Inter-Organizational levels* " has been accepted and presented at the 26th IFIP/SOCOLNET Working Conference on Virtual Enterprises PRO-VE 2025.

3.3 Conceptual Modeling

Conceptual modeling plays a central methodological role in this dissertation by supporting the structured representation of knowledge necessary for the development of the GenAI-Enhanced Knowledge Management Framework (GAKMF). As (Guarino et al., 2020) emphasize, conceptual models are explicit representations of mental models grounded in intentional abstractions, not direct depictions of data, and serve to clarify the meaning of concepts and their interrelations.

Furthermore, authors (Thalheim, 2019) highlight that effective conceptual models must reflect cognitively and contextually meaningful structures rather than merely enumerating domain terms, highlighting the importance of completeness, semantic coherence, and conceptual grounding.

Adhering to these foundational principles, conceptual models were developed for each individual domain (KM, IM, DM, DG) and their interactions with GenAI (IM/GenAI/KM and DM/GenAI/DG) to deepen understanding and facilitate framework development. Conceptual modeling, therefore, serves as a critical method for deliberately describing the conceptualized reality within this research (Guarino et al., 2020).

This research adopts a "lightweight" conceptual modeling approach, combining principles from ontology engineering and knowledge organization. Conceptual models are to be constructed through the following steps:

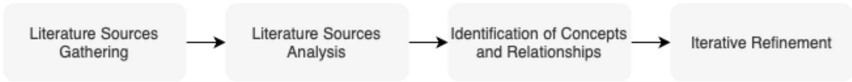

Figure 3.4: Conceptual Modeling Steps

1. **Literature Sources Gathering:**

   The first phase consisted of identifying and gathering academic sources to establish a comprehensive knowledge base for each domain. Retrieved articles were meticulously organized using Zotero, a tool that facilitated efficient organization and retrieval through a taxonomy. Scientific articles were primarily sourced from leading databases, including Scopus, Web of Science, Emerald Insight, Sage Journals, AIS eLibrary, Springer. Additionally, this corpus was further complemented by foundational texts in Knowledge Management (Davenport; Prusak, 1998; Ikujiro Nonaka; Takeuchi, 1995; Dalkir, 2023), Data Management and Governance (Susan Earley et al., 2017), Information Management (Chun Wei Choo, 2002), and more recent works on AI and GenAI (Davenport, 2018; Oliveira, 2025). The inclusion criteria prioritized relevance to the dissertation's research questions and objectives, organizational context, theoretical contribution, and conceptual clarity. This comprehensive corpus provided the foundational material for domain understanding and subsequent concept extraction.

2. **Literature Sources Analysis:**

   The second phase involved the analytical and interpretive reading of the collected materials. An initial, more superficial approach focused on reading abstracts, results, and conclusions to identify and select articles directly pertinent to the dissertation's research purpose. Subsequently, the most relevant articles underwent a deeper exploration to uncover relationships and expand knowledge across disciplines, fields, concepts, and narratives. This deep reading enabled the extraction of meaningful conceptual elements beyond surface-level terminology. The curation of sources was directly guided by the need to address the dissertation's problems and objectives, ensuring that all selected material contributed to the creation of the artifacts.

3. **Identification of Concepts and Relationships:**

   Following the Design Science Research (DSR) paradigm and building upon insights from problem identification, motivation, and objectives (as part of the DSRM processes), the third phase involved the selective abstraction of concepts and relationships. These were deemed most relevant to the specific problem context of this dissertation: the integration of GenAI into knowledge management processes within organizations, specifically addressing the inter-dependencies that enable its effective function and adoption. In this phase, the knowledge acquired from the comprehensive reading and analysis of scientific papers and books was critical to identify the most relevant concepts and relations pertinent to the dissertation's context.

4. **Iterative Refinement:**

Adhering to the DSR design cycle, conceptual models underwent iterative refinement. This process was driven by analytical evaluation and feedback from domain experts. Rather than aiming for exhaustive representations, the conceptual models were designed as purposeful abstractions that serve the goals of this research artifact. The modeling followed semantic clarity principles, replacing ambiguous or generic connectors, such as has and is, with specific relationships, such as "enables", "governs" to ensure interpretation is clear and representing real-world dynamics. Each model was designed to highlight how its respective domain interacts with GenAI and contributes to the transformation of KM processes and organizational performance.

3.4 The Sociotechnical System Theory

Sociotechnical Systems (STS) provides a foundational lens for understanding and designing complex organizational systems comprising both social (human-driven) and technical (technology-driven). (Baxter et al., 2011). The theory originated from the Tavistock Institute's studies in the 1950s, emphasizing the joint optimization of social and technical subsystems to enhance both organizational performance and the quality of the worker's life. In contemporary contexts, especially amidst current digital transformations, STS theory remains paramount for integrating advanced technologies — such as Generative AI — into organizational structures in a responsible and effective manner (Baxter et al., 2011; Sony et al., 2020).

The implementation of GenAI in KM processes, considering DG, DM, and IM represents a paradigmatic case for the application of STS. As (Baxter et al., 2011) highlight, sociotechnical systems design recognizes that technical solutions, when implemented in isolation from their social context, risk being misaligned with actual work practices and user needs. Similarly, authors (Sony et al., 2020) argue that technologies aligned with i4.0 — such as AI, cyber-physical systems, and IoT — require a proper architecture grounded in STS principles to ensure sustainable implementation.

While STS theory's full potential has yet to be explored, the importance to apply this theory into the artifact is highly relevant given current technological and societal context. The STS approach provides a foundational perspective on how this technology can be effectively used with respect to different factors, particularly in integrating GenAI into KM, where human cognition, work roles, and collaboration (social system) intersect significantly with digital infrastructure, processes, and AI capabilities (technical system).

Chapter 4

The Conceptual Relation: IM, KM, DM, DG and GenAI

As the author (Chun Wei Choo, 2002) states in the book "Information Management for the Intelligent Organization: The Art of Scanning the Environment": "Organizations are societies of minds. Actions and decisions are not the simple outcome of any single, orderly activity: they emerge from an ecology of information processes". Across organizations information is intrinsic to every process and activity essential for decision-making. Organizations commit to specific objectives and goals, aiming to enhance their services, products, and organizational processes. Consequently, gaining insights about the industry, customers, and the market becomes necessary to maintain competitive advantage (C. W. Choo, 1996). How are these objectives achieved?

This chapter introduces the relationship among the disciplines of Information Management (IM), Knowledge Management (KM), Data Management (DM), Data Governance (DG), and Generative AI (GenAI). As indicated in the previous chapter, it is impossible to discuss knowledge management without connecting it with information management since data transforms into information, and information into knowledge. As emphasized by (Payne et al., 2020), it is paramount that clear distinction of both disciplines is framed, since it contributes to good practices — managers should understand and value the role of information and knowledge management respectively. Authors (Kruger et al., 2010) further highlight that Information and Communications Technology (ICT) and IM are foundational to KM, viewing them as prerequisites and enablers of the discipline.

4.1 Information Management and Knowledge Management

Information must be properly created, organized, processed, and used for individuals to create knowledge that leads to valuable decisions (C. W. Choo, 1996; Detlor, 2010). Currently, leveraging an organization demands constant and urgent attention to market shifts, environmental disruptions, and technological innovations (Chun Wei Choo, 2002; Amankwah-Amoah et al., 2024; Kaczorowska-Spychalska et al., 2024; Herrmann et al., 2023). The foundational principles that

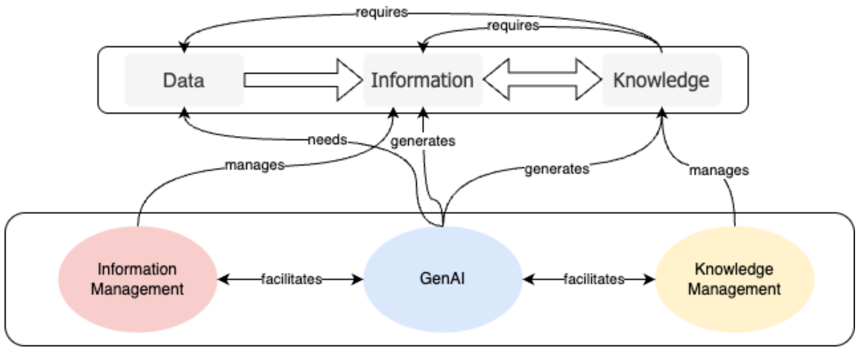

Figure 4.1: Relationship between IM, GenAI, and KM with Data, Information and Knowledge.

organizations historically applied to enhance processes and success remain pertinent: "...survivability is dependent on the organization's ability to process information about the environment, and to turn this information into knowledge that enables it to adapt effectively to external change" (Chun Wei Choo, 2002). This context leads to contemporary technological advancements, such as the introduction of Generative AI, a tool capable of redesigning information and knowledge processes by generating human-like content, potentially influencing organizational productivity and efficiency (Prasad Agrawal, 2024; Amankwah-Amoah et al., 2024).

The discussion around information and knowledge management is particularly relevant in the era of GenAI, as its capabilities blur traditional boundaries, introducing new opportunities and significant challenges (Payne et al., 2020; Alavi; D. Leidner, et al., 2024). As previously discussed, (Alavi; D. Leidner, et al., 2024) suggests that GenAI is capable of compressing the information layer by automatically transforming data into knowledge. It seems that GenAI changed the paradigm by its capacity to generate knowledge — a worker can rapidly encounter critical insights and recommendations for decision-making without the need to deal with information and cognitive overload challenges (Benbya; Deakin University, et al., 2024; Alavi; D. Leidner, et al., 2024; Chowdhury et al., 2022). However, (Payne et al., 2020) raises questions about the knowledge generated by machine intelligence, arguing that machines do not generate knowledge but information, as it must be understood by human intelligence to be considered knowledge. This author presents the main differences between KM and IM, referring how knowledge does not exist without people, contrary to information, that, once created, exists by itself. Knowledge serves decisions and actions, while information is an input for knowledge that also needs the knowledge from individuals to be transformed. Therefore, these conflicting considerations pose even more questions: What is the role of information management and knowledge management in this world of intelligent tools capable of generating human-like outputs? What is the impact of GenAI on these disciplines within various organizational settings?

In figure 4.1, a visual representation of each discipline is presented in relation to GenAI technology and the elements data, information, and knowledge. This combination, based on (Rowley, 2007) and (Payne et al., 2020), aims to support the literature review from the previous chapter and introduce the objectives of the current chapter. The DIKW Hierarchy (Data-Information-

Knowledge-Wisdom), originally created by "Ackoff's article titled *From data to wisdom*" is discussed by (Rowley, 2007), who presents different variations of the relationship between data, information, knowledge, and wisdom by different authors. This hierarchy describes this progression where data is transformed into information for a specific purpose or context, thereby giving meaning and utility. Subsequently, information is transformed into knowledge, encompassing deeper understanding and capability derived from human cognition. Author (Payne et al., 2020) extends this hierarchy with contemporary considerations, incorporating machine learning and concepts such as artificial knowledge. As previously mentioned, (Payne et al., 2020) emphasizes that transforming data into knowledge and vice versa inherently requires existing knowledge. Additionally, the author notes that information and knowledge can interchangeably transform; codified knowledge becomes information when articulated through words, images, or symbols. Consequently, Information Management (IM) addresses the lifecycle of information, including its creation, acquisition, organization, storage, distribution, and use (Detlor, 2010), whereas Knowledge Management (KM) handles knowledge through creation, storage and retrieval, transfer and sharing, and application (Alavi; D. E. Leidner, 2001).

Information Management is a crucial discipline that helps organizations identify and address business needs by systematically managing the entire information lifecycle (C. W. Choo, 1996; Chun Wei Choo, 2002). Organizations thereby are able to clearly identify their information requirements, recognize existing gaps, and utilize information effectively within organizational processes. Moreover, IM not only helps to understand and support the information needs of the organization but also those of all the "key constituencies that compose the organization" (Chun Wei Choo, 2002).

Presently, the important and transformative element is Generative AI, capable of generating knowledge and information (considering (Payne et al., 2020)'s lens) through diverse outputs, facilitating IM and KM processes. Notwithstanding, GenAI can also be facilitated by IM and KM, specifically in the design and employment of this technology within organizations.

However, addressing information and knowledge management in the context of cognitive technologies such as GenAI introduces challenges associated with its integration. Organizations aspire to implement this technology, yet numerous factors hinder their advancement. Author (Davenport, 2018) highlights that "the availability of high-quality and high-volume data is particularly important for any machine learning-based applications", meaning that "data should be clean, consistent, and well-integrated throughout the organization". One of the most crucial factors for the efficient employment of cognitive technologies, such as GenAI, is the access to high-quality data (Haridasan et al., 2024). Thus, if organizations are not investing in data management and governance strategies, they will encounter problems such as inadequate data for training, inaccurate and biased outputs, hallucinations and unreliability (Haridasan et al., 2024; Kaczorowska-Spychalska et al., 2024; Amankwah-Amoah et al., 2024; Aromaa et al., 2025; Dwivedi; Hughes, et al., 2021; Janssen, 2025; Taeihagh, 2025). Surprisingly, most companies assume their data is ready to implement AI technologies when, in reality, it is in poor conditions. Studies reveals a significant difference between perception and reality — it seems that organizations are not implementing strategies to manage data required for AI to efficiently work (AIIM, 2024). Given these integration challenges, the relevance of Data Management (DM), Data Governance (DG), and Information Management (IM) is extremely elevated. Therefore, what is data management and data governance? Why are they necessary for GenAI and, consequently, KM processes?

4.2 Data Management and Data Governance

According to (Susan Earley et al., 2017), Data Management is "the development, execution, and supervision of plans, policies, programs, and practices that deliver, control, protect, and enhance the value of data and information assets throughout their lifecycles". Data Governance, on the other hand, is defined as the "exercise of authority and control (planning, implementation, monitoring, and enforcement) over the management of data assets", which means that DG focuses on "how decisions are made about data and how people and processes are expected to behave in relation to data". Data governance works as an enabler of data management, assuring that "all operational functions of data management contribute to the achievement of business vision, mission, and strategy". It directly "impacts decision rights and accountability for data-related processes" (Karkošková, 2023). Collectively, these disciplines significantly help organizations achieving their goals, particularly in integrating GenAI, which relies on data volume and quality to perform effectively (Akhtar et al., 2024).

GenAI models are inherently data-driven, depending entirely on high-quality data for effective adoption within business contexts (Banh et al., 2023). Given GenAI's intended role in numerous tasks influencing decision-making and organizational success, data quality and availability are a primary and central focus for its positive outcome. As emphasized by (Haridasan et al., 2024), "inconsistent or low-quality data can result in inaccurate generative models, reducing their effectiveness". Furthermore, significant disparities exist between large companies and small-to-medium enterprises regarding data availability and quality. A prevalent issue among small and medium-sized enterprises is inadequate data quality — often incomplete or unstructured — which severely hinders the process of training GenAI models (De Simone et al., 2023).

What happens when data is poor and scarce? Bias and hallucinations problems appear, leading to unfair and unreliable results (Banh et al., 2023; Alavi; D. Leidner, et al., 2024; Dwivedi; Kshetri, et al., 2023; Q. Zhang et al., 2025). Such inaccuracies can severely impact users and organizations. An example is given by (Banh et al., 2023), that if GenAI is being used for product recommendations, it can impact results "ranging from selecting the wrong product to taking the wrong medication". Consequently, organizations must implement sturdy strategies to "prevent, detect, and mitigate biases", deeply understanding how the outputs of these models "think" and "decide" to ensure service quality, protect users and businesses, while also achieving goals responsibly.

In addressing these challenges, human intervention remains indispensable to mitigate potential risks. Human oversight ensures GenAI models generate plausible and accurate content (Banh et al., 2023). This also aligns with a human-AI collaboration approach, where humans are always the central focus, necessary to control and oversight intelligent cognitive technologies (Kumar et al., 2025). As (Waschull et al., 2023) articulate, "human work extends to cognitive tasks linked to AI, including collecting and annotating data, interacting with intelligent systems to enrich their knowledge, as well as tuning or maintaining them". Thus, the human role is essential for achieving successful human-AI symbiosis.

Considering additional challenges related to GenAI, as previously mentioned in section 2.4, the integration and utilization of GenAI also introduce significant security and privacy concerns. Relying on vast amounts of data, collected from different sources within manufacturing processes, questions are raised regarding how data is stored, shared, and utilized. Access to diverse data types, including sensitive and confidential ones, poses numerous security risks (Shafiee, 2025; Taeihagh, 2025). It is imperative that organizations align their data practices with regulations and standards to mitigate potential risks (Haridasan et al., 2024) and implement robust data storage and access control measures (Shafiee, 2025).

Given these potential challenges associated with developing, integrating, and applying GenAI within organizational and manufacturing settings, one might infer that in addition to information and knowledge management, the disciplines data management and data governance are at the center of the discussion, considered a requirement to embrace this technology. Consequently, how can these relevant and essential disciplines effectively mitigate the associated risks?

Figure 4.2 provides a conceptual representation illustrating the relationships between Data Management (DM), Data Governance (DG), data, and Generative AI (GenAI), positioning each component within an interdependent and hierarchical system of influence. This conceptual structure aligns with principles outlined in (Susan Earley et al., 2017). Understanding this relationship is crucial for organizations to grasp the distinct roles of each discipline and their essential interaction with GenAI. These two disciplines function complementarily yet distinctly: DM is about putting data to use and data governance is about overseeing how that happens. Data, placed at the center of the diagram, highlights its dual nature as both a managed and a governed asset. The positioning of data reinforces the necessity of a dual control: it must be technically managed for usability within GenAI and strategically governed for risk mitigation associated with the technology. Both DM and DG converge on data as their central concern, with GenAI conceptualized as the "consumer" and amplifier of data.

Regarding data management, the discipline is represented by its responsibility to "ensure" data quality, architecture, metadata management, and security/privacy in the GenAI landscape. Without proper data management, the foundation for GenAI's learning is compromised as they rely exclusively on extensive volumes of input data (Jarrahi et al., 2023; Akhtar et al., 2024).

Conversely, data governance, positioned on the opposite side of the diagram, establishes the conditions under which data is governed, which, consequently, regulates GenAI. These functions reflect the governance role defined in (Susan Earley et al., 2017), which encompasses setting policies and standards, defining clear roles and responsibilities, ensuring compliance with legal and ethical requirements, and maintaining oversight mechanisms such as stewardship and accountability structures. DG focuses on decision-making processes related to data and identifying respon-

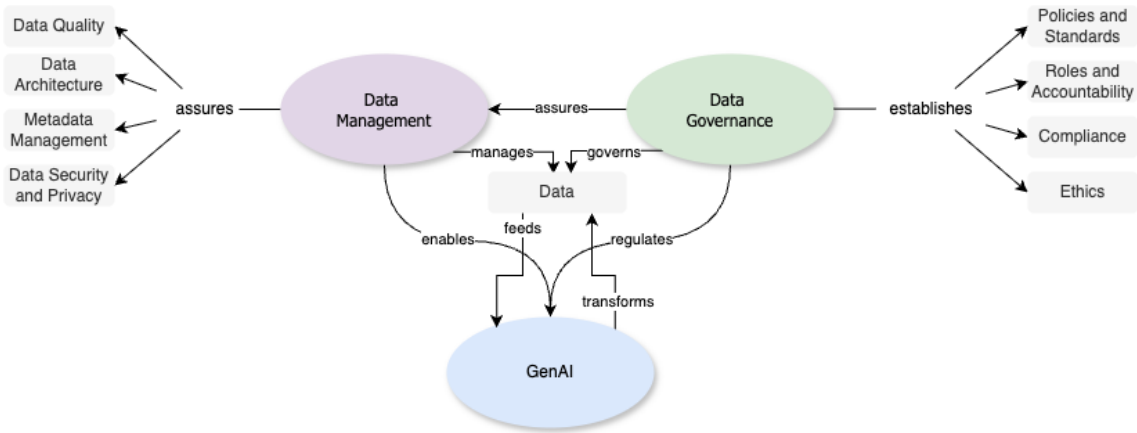

Figure 4.2: Relationship between DM, GenAI, DG and Data.

sible entities (Abraham et al., 2019). According to (Taeihagh, 2025), given the "high levels of technological and economic uncertainty surrounding the development of generative AI, the governance of generative AI is of paramount importance to ensure such systems' ethical and responsible use". It is mandatory that challenges associated with GenAI don't transfer to society, which, due to its black box nature, can easily raise questions about transparency, accountability, and liability. Once again, certain companies possess informational and technical advantages, which are extremely helpful to develop governance strategies, such as "antitrust policies, transparency requirements, and public engagement". Moreover, a very important aspect in the integration and application of GenAi within organizations is the often technocratic view, leading to a lack of comprehension on how this technology aligns with societal values and how it affects people. It is not only about the creation of laws and regulation, but also to inform all the related members to ensure the technology is controlled in responsible ways (Taeihagh, 2025).

As a conclusion, the integration of GenAI into organizational settings reinforces the urgency of embedding robust data management and data governance practices and strategies into the strategic core of technological development.

In the next section, conceptual representations for each discipline — Information Management, Knowledge Management, Data Management, Data Governance, and Generative AI — is presented based on the literature review. These representations act as a contribute to the understanding of the domain, their concepts and relationships, which will serve as a base for the creation of the artifact of this dissertation.

4.3 Conceptual Models: Construction

The development of conceptual models for the foundational disciplines addressed in this dissertation — Information Management, Knowledge Management, Data Management, Data Governance, and Generative AI — is a critical methodological step thoroughly addressed in chapter 4. Each conceptual model serves as a cognitive stand, facilitating the identification and integration of key domain concepts, their attributes, and interrelationships.

Constructing these models is important for several reasons. First, they assist in clarifying the scope and conceptual boundaries within each discipline. Second, these conceptual models provide a foundational basis for developing an artifact that explores GenAI's impacts on KM processes and its interactions with the other disciplines, aiming to inform organizations about critical considerations in developing, integrating, and using this technology to achieve organizational advantage. Lastly, they provide an analytical lens to examine each domain individually, thus establishing a structured foundation for subsequent stages of the research.

The conceptual representations are as follows:

- Information Management: Figure 4.3 - Conceptual Representation of Information Management
- Knowledge Management: Figure 4.4 - Conceptual Representation of Knowledge Management
- Data Management: Figure 4.5 — Conceptual Representation of Data Management.
- Data Governance: Figure 4.6 - Conceptual Representation of Data Governance.
- Generative AI: Figure 4.7 - Conceptual Representation of Generative AI.
- Knowledge Creation: Figure 4.8 — Conceptual Representation of Knowledge Creation Process.
- Knowledge Transfer and Sharing: Figure 4.9 - Conceptual Representation of Knowledge Transfer and Sharing Process.
- Knowledge Storage and Retrieval: Figure 4.10 - Conceptual Representation of Knowledge Storage and Retrieval Process.
- Knowledge Application: Figure 4.11 - Conceptual Representation of Knowledge Application Process.

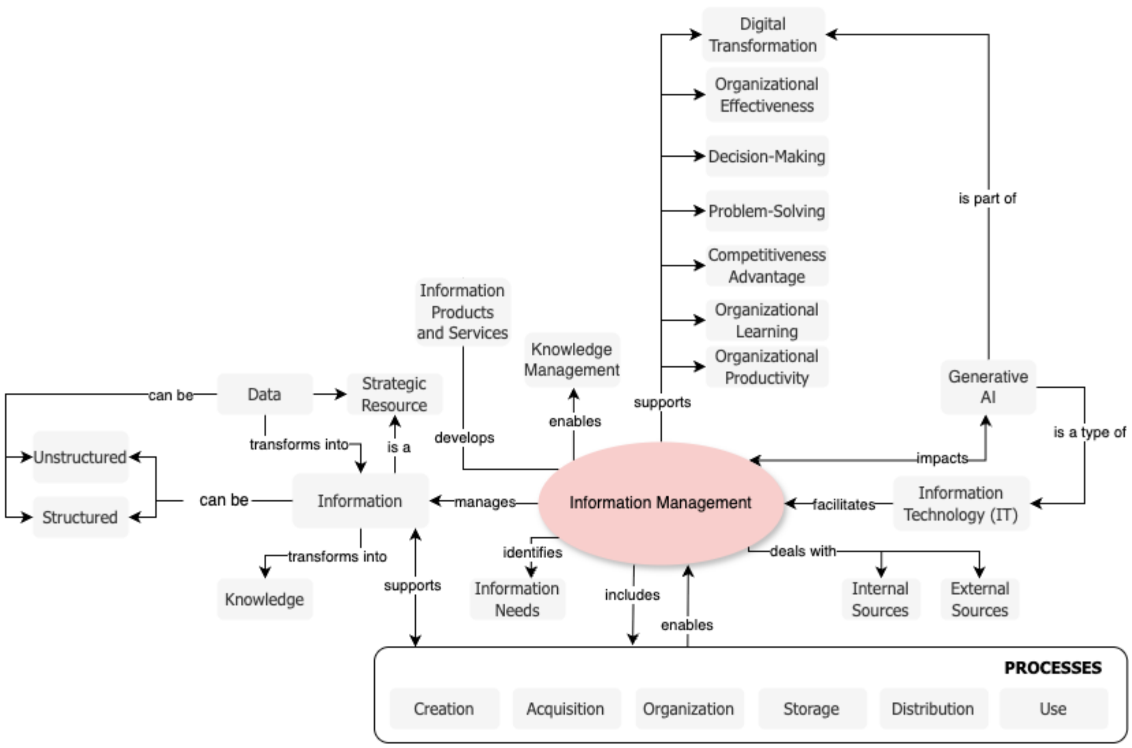

Figure 4.3: Conceptual Representation of Information Management.

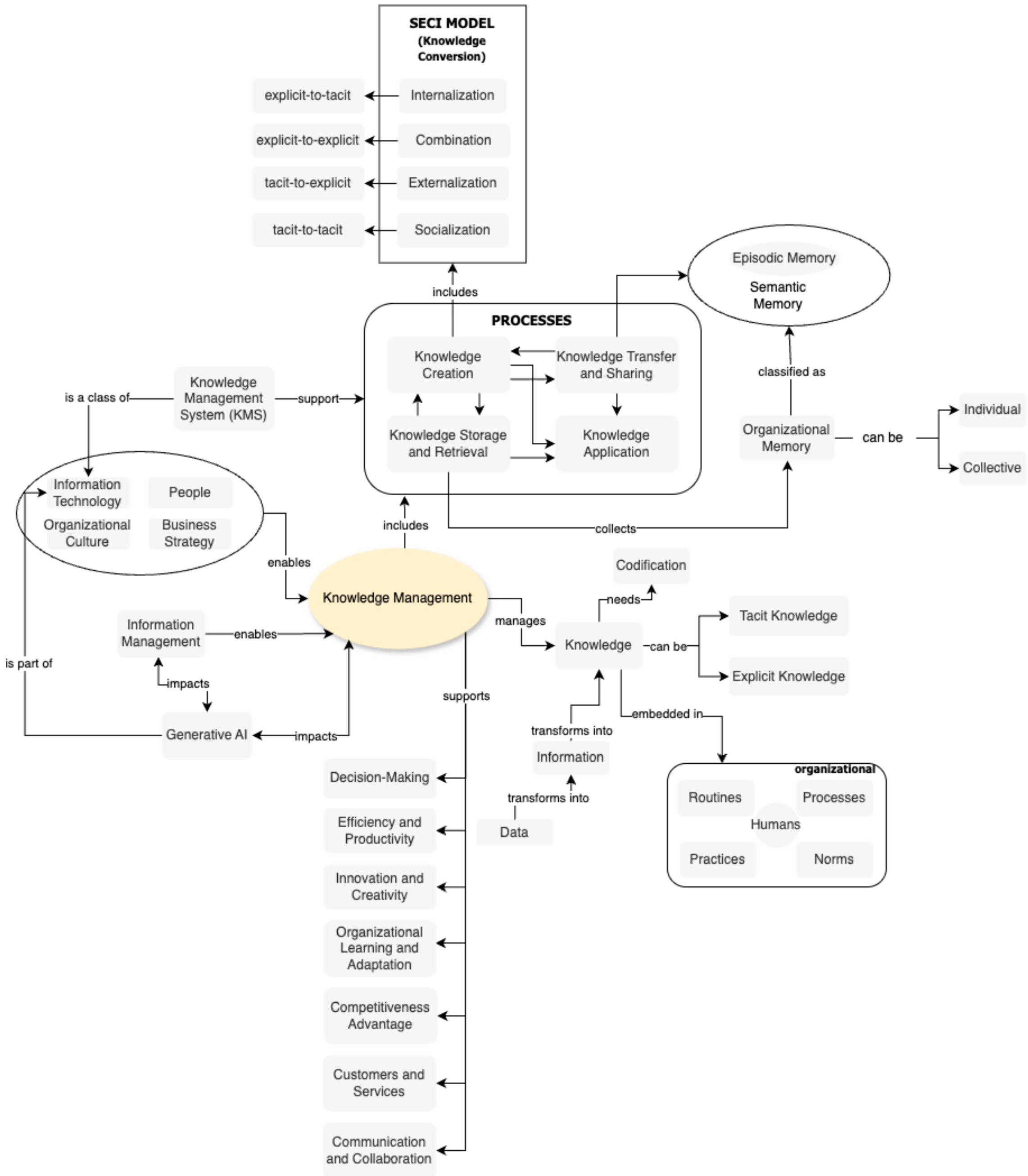

Figure 4.4: Conceptual Representation of Knowledge Management.

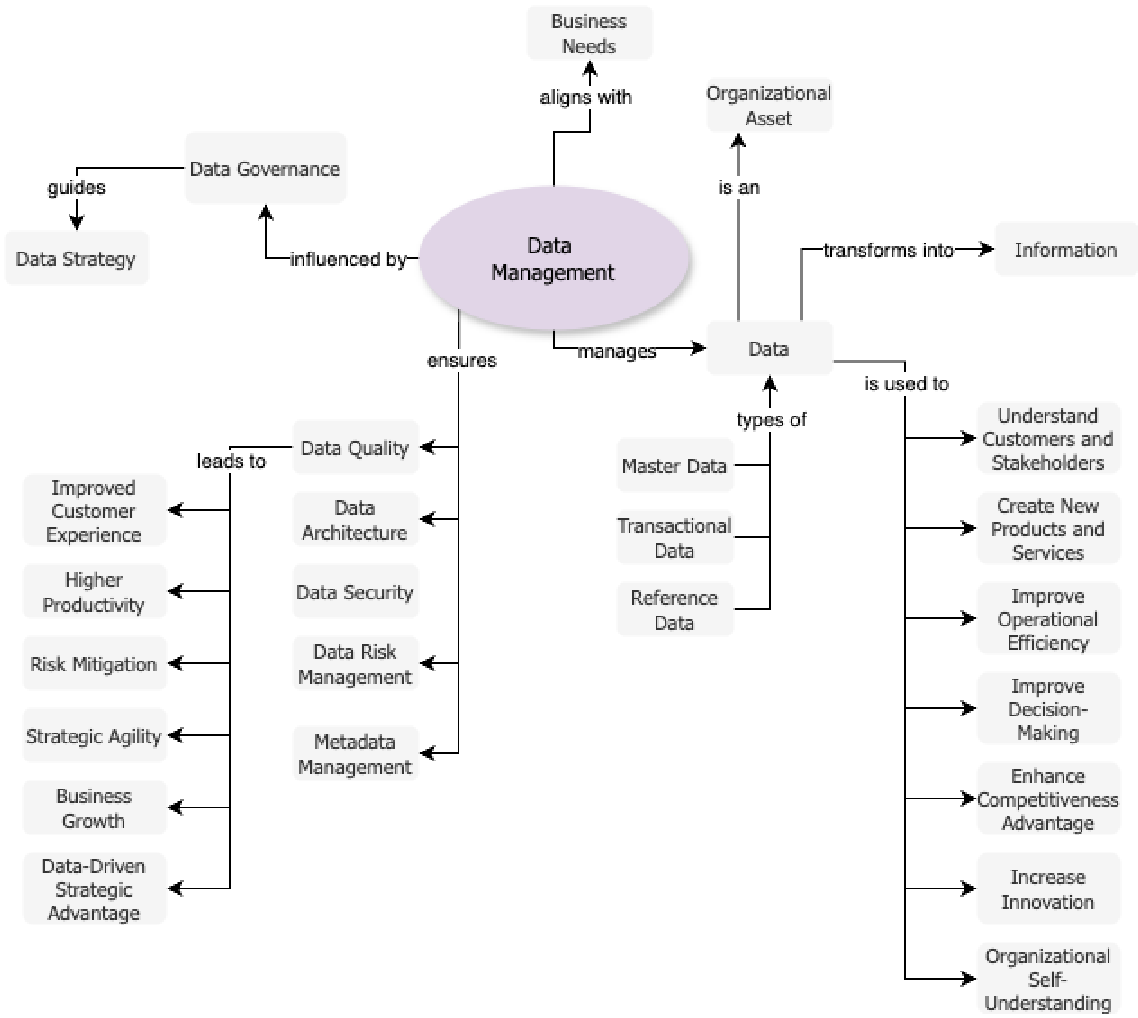

Figure 4.5: Conceptual Representation of Data Management.

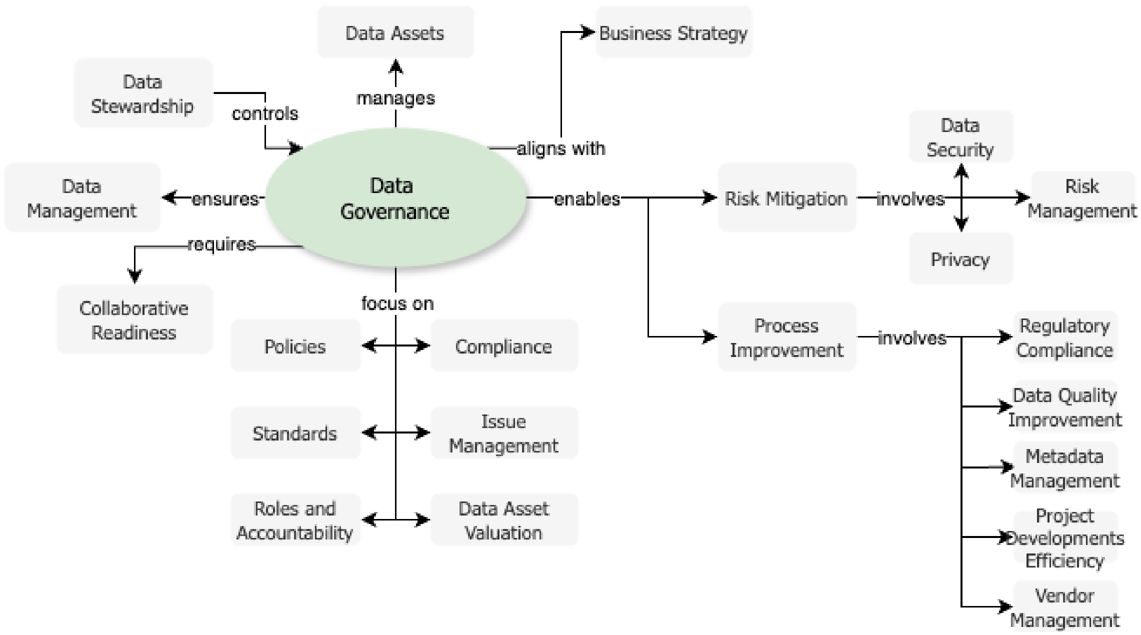

Figure 4.6: Conceptual Representation of Data Governance.

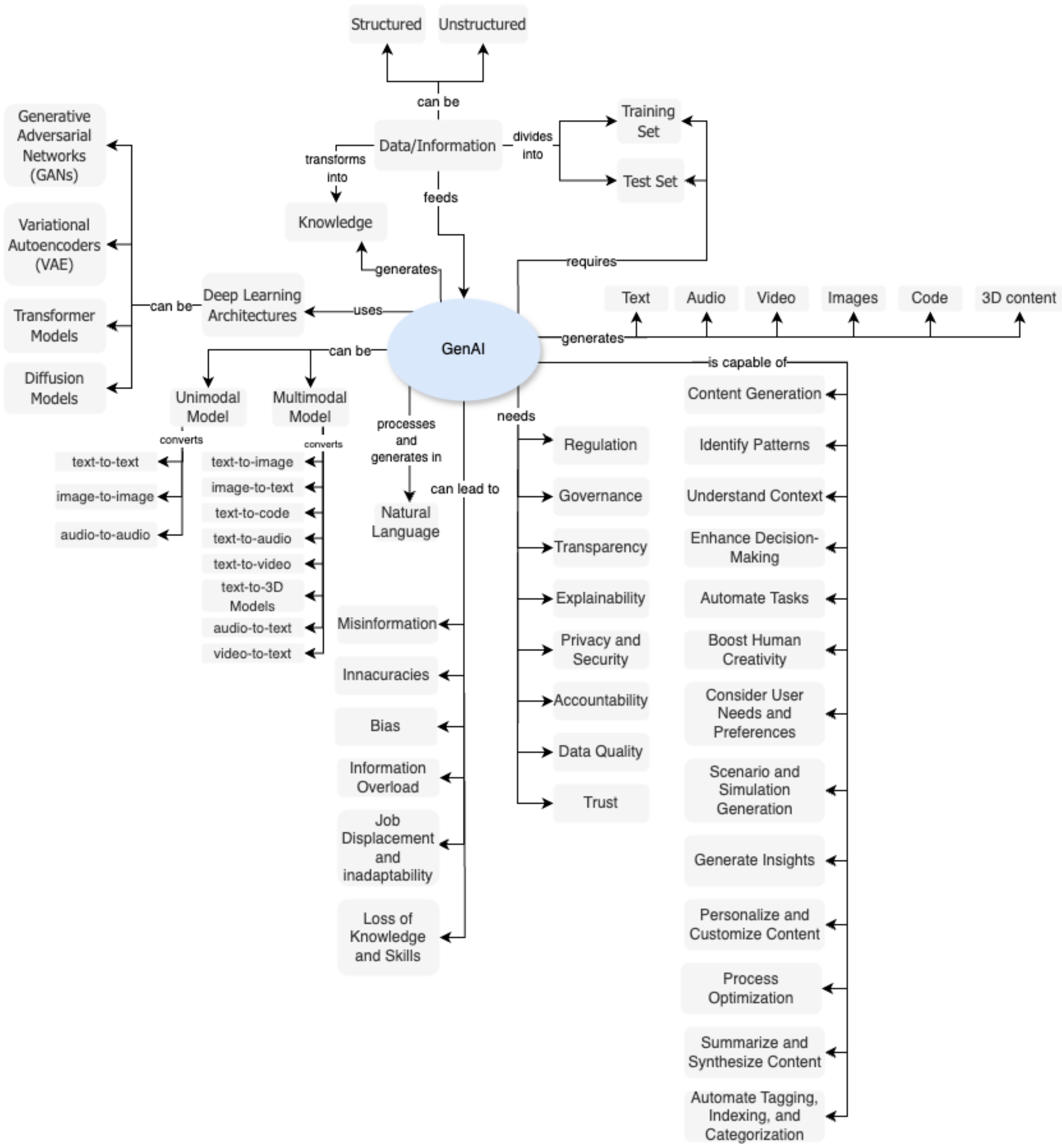

Figure 4.7: Conceptual Representation of Generative AI.

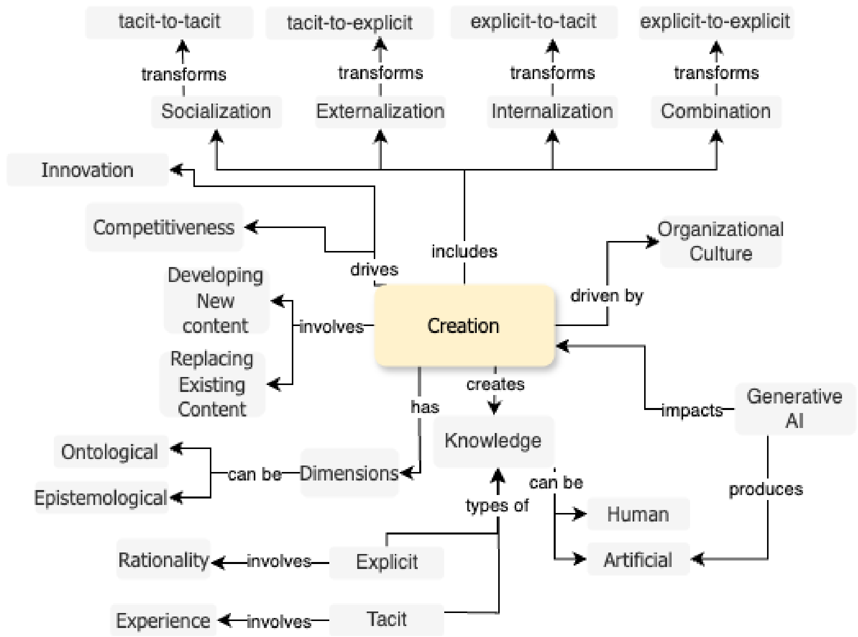

Figure 4.8: Conceptual Representation of Knowledge Creation Process.

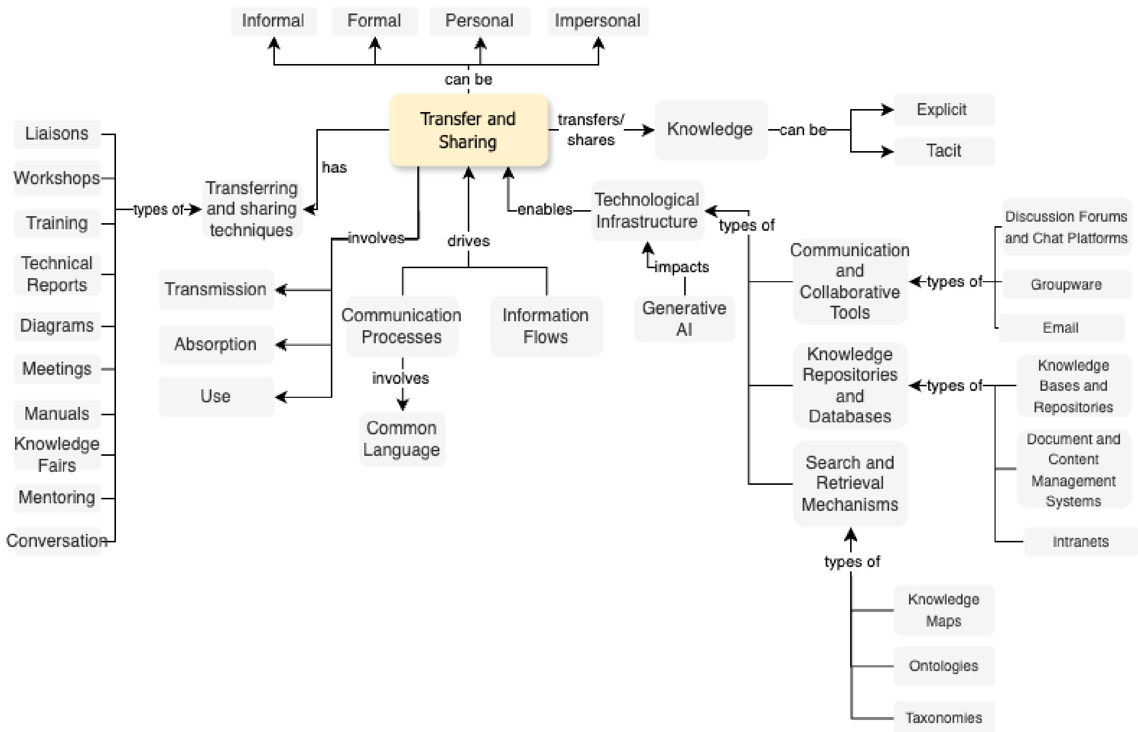

Figure 4.9: Conceptual Representation of Knowledge Transfer and Sharing Process.

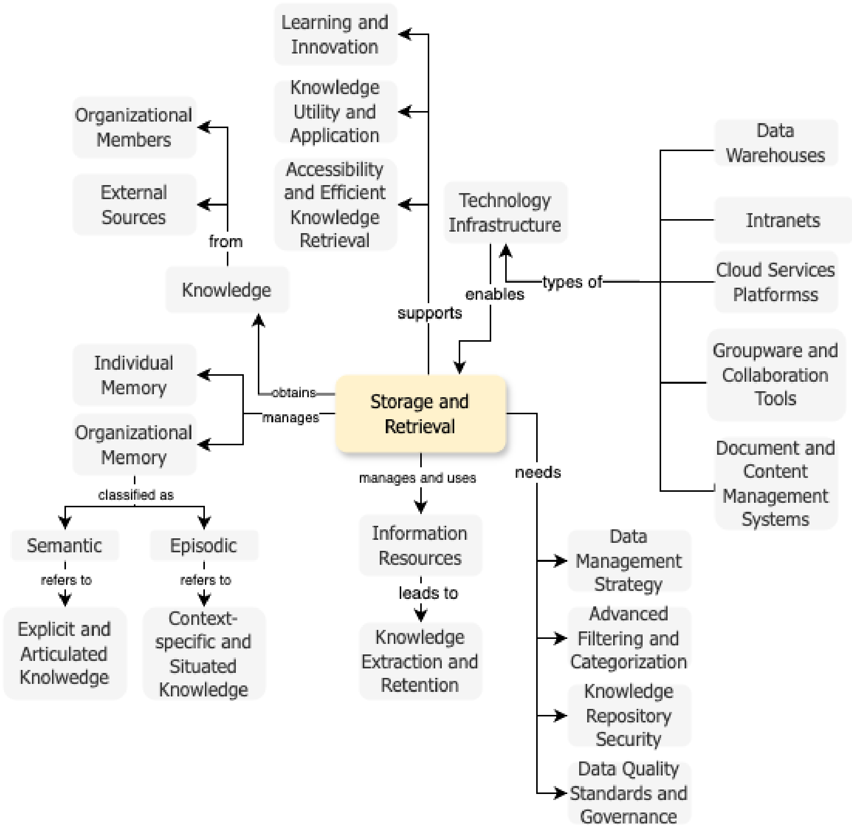

Figure 4.10: Conceptual Representation of Knowledge Storage and Retrieval Process.

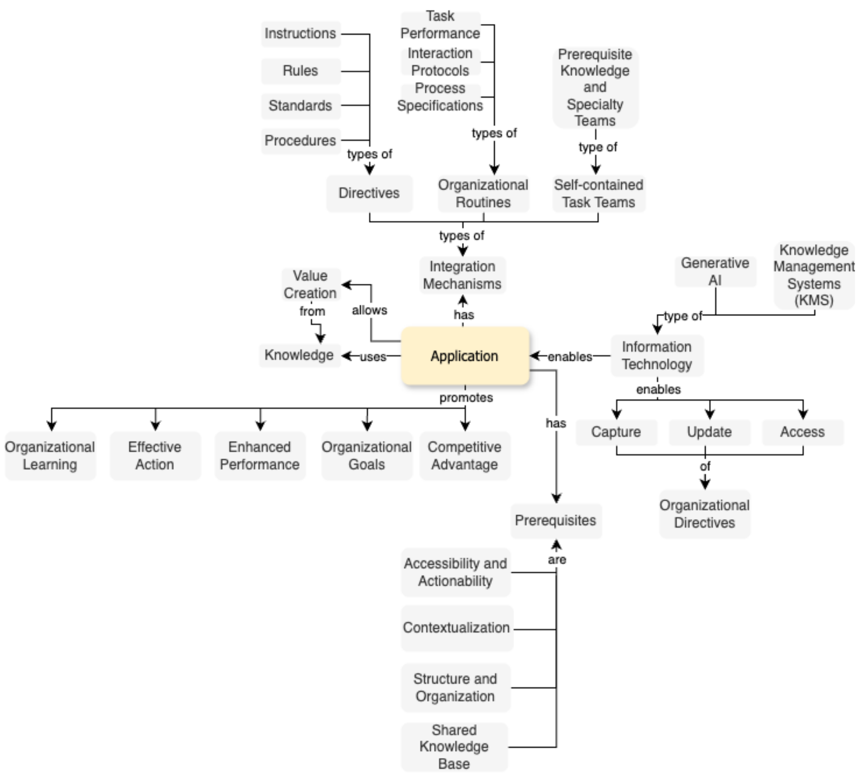

Figure 4.11: Conceptual Representation of Knowledge Application Process.

Chapter 5

Generative AI-Enhanced Knowledge Management Framework

This chapter presents a conceptual framework developed as a core artifact of this dissertation. The framework is the result of an extensive literature review and critical synthesis conducted in previous chapters. It is designed to guide researchers, practitioners, and organizations in understanding the key considerations necessary for the effective and responsible implementation of GenAI, which a specific focus on its implications for Knowledge Management processes. The framework emphasizes achieving optimal outcomes within organizational environments by integrating strategic, technical, and social perspectives.

5.1 The Framework GAKMF: Overview

The Generative AI-Enhanced Knowledge Management Framework (GAKMF) offers a multi-layered view of how GenAI can be effectively embedded within organizational knowledge environments, while considering a sociotechnical perspective. It brings together strategic foundations, data and governance strategies/measures, GenAI capabilities operating within a social and technical system, knowledge processes impacted by GenAI, and anticipated organizational outputs.

The framework is structured across five main levels:

- **Organization Strategic Definition Level:**

This level defines the strategic organizational foundations necessary for the responsible integration of GenAI into the organization. It includes the identification of business needs, valuation of data and information, along with the support of information management and the relationship with data management and data governance practices. This level ensures that GenAI adoption is purposeful, aligned with business objectives, and strategically guided.

- **Data and Ethical Preparation Level:**

This layer ensures the quality, integrity, and ethical management of data and information before it is processed or generated by AI systems. It encompasses robust data management practices, such as metadata standardization, accuracy assurance, and storage reliability, as well as ethical governance, including transparency, compliance, security, and measures to mitigate societal risks and maintain trust.

- **GenAI System in a Sociotechnical Context Level:**

Positioned in the middle of the framework, this level captures the interaction between the GenAI system and the KM processes within a sociotechnical system. GenAI capabilities are identified as cognitive emulation, human-like interaction, generative multimodal output, and contextual adaptability. Considering the sociotechnical system theory, although the application of this theory is mostly superficial, it is intended to give importance to a sociotechnical lens in this context, opening the possibility for continuous evolution of a theoretical side through a more profound and focused research in the future. GenAI operates within both technical infrastructures (e.g., KM platforms, processes, and data and ethical considerations) and social structures (e.g., human roles, communication, and trust), mediated through a human–machine feedback loop.

- **Knowledge Management Processes Enhanced by GenAI Level:**

This level articulates how GenAI transforms the four core KM processes: knowledge creation, storage and retrieval, transfer and sharing, and application. GenAI augments human creativity, accelerates knowledge flows, improves accessibility and personalization, and enables more effective decision-making by generating, organizing, and delivering contextually relevant knowledge to workers within organizational and industrial settings.

- **Organizational Expected Results Level:**

The final level outlines the expected organizational outcomes resulting from GenAI-enhanced KM. These outcomes include improved performance and innovation, strategic agility, ethical and sustainable knowledge practices, human-centric workforce empowerment, and alignment with the values and principles of Industry 5.0.

5.2 Demonstration and Analysis of the Generative AI-Enhanced Knowledge Management Framework (GAKMF)

5.2.1 Organization Strategic Definition Level

The first level of this framework "*Organization Strategic Definition*", provides foundational guidance for aligning GenAI with the organizational strategy and for comprehensively understanding both internal and external environments. This stage ensures that GenAI adoption is purposeful, well-planned, and integrated, rather than just a technological pursuit (Akbarighatar et al., 2023).

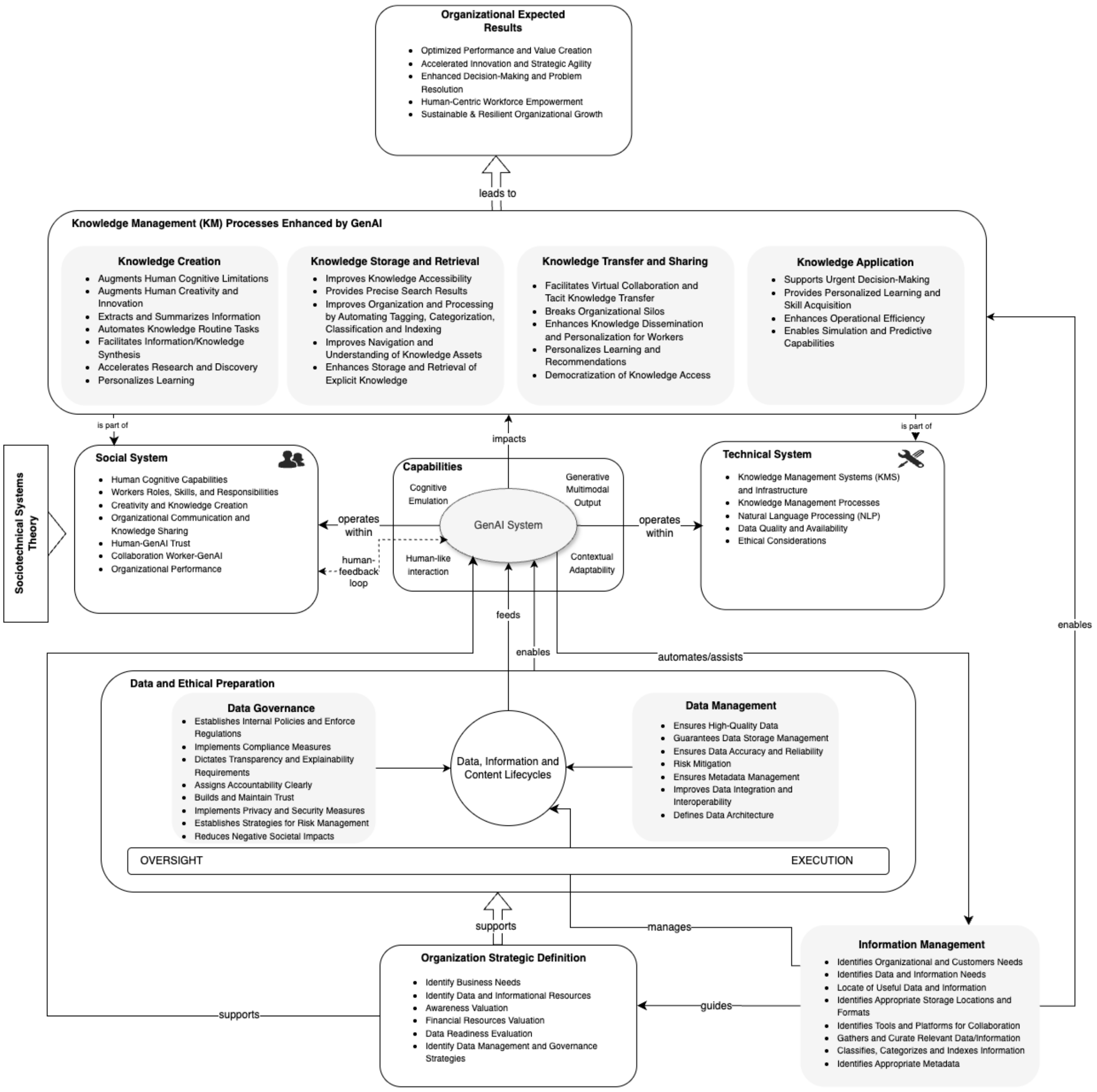

Figure 5.1: Generative AI-Enhanced Knowledge Management Framework (GAKMF)

Organizations interested in implementing GenAI tools need to consider several factors that directly influence outcomes. As author (Davenport, 2018) states, "one key decision that almost every organization faces with cognitive technology is where in the business to apply it". He follows with this important question: "What business problems, issues, or opportunities can benefit from the use of cognitive technologies?".

Organizations may recognize that knowledge and insight is needed to manage all assets and specifications to apply an emergent technology such as GenAI, yet they lack real perception of how to effectively start and prepare the organization. As a result, based on the literature, a set of activities crucial to establish and evaluate the integration of GenAI within an information and organizational perspective is elaborated.

By defining an initial strategic definition, organizations start to rationalize their possibilities in developing and employing GenAI within the organization, which consequently, affects the effectiveness of knowledge management processes. Clear objectives must be set and aligned with business goals when adopting AI technologies (Soares et al., 2024). Identifying business needs leads the organization to visualize and comprehend how this technology can be helpful to their business processes and expected results. According to (Chun Wei Choo, 2002), "in the identification of information needs, organization members recognize the volatility of the environment, and seek information about its salient features in order to make sense of the situation, and to have the necessary information to take decisions and solve problems". This affirmation is extremely relevant to support any novel decision, such as the introduction of a new technology into the organization. A decision such as the development, integration, and use of a technology needs to be considered with extreme caution and evaluation of the needs. As an example, a lot of organizations are interested in applying GenAI, but they don't truly comprehend if they actually can and need the technology or, in contrast, to what business processes they can and should implement it (Chowdhury et al., 2022; Dwivedi; Hughes, et al., 2021). In addition, as mentioned in the literature, organizations need to identify their data and informational resources in combination to a data readiness and technological infrastructure evaluation combined with a financial resources valuation. Why is this important? GenAI is a technology that relies solely on data, which leads to results based on that same data. Concurrently, GenAI models are computationally intensive, requiring expensive hardware and power (Aromaa et al., 2025), which is a barrier for organizations, specifically for smaller manufacturing firms (M. Ghobakhloo et al., 2024). For that, organizations need to evaluate their financial resources to discern their GenAI's adoption possibilities considering factors such as financial resources availability and how much data they possess as well as its condition. Understanding which business processes are in need and what results are expected, informs the organization about the path they need to follow, what investment can be made. Data readiness is related to the assurance that organizations hold data in great conditions in terms of quality and availability (Akbarighatar et al., 2023; Davenport, 2018). Here, the identification of data management and governance strategies is essential to accompany the problems and challenges associated with the data.

The next level "Data and Ethic considerations" will focus on the application of data governance and data management strategies, including the activities that contribute to its efficiency and applicability on this organizational and technological context. Organizations must apply robust data governance methods and develop a data management strategy to protect and leverage this technology (Leoni et al., 2024; M. Ghobakhloo et al., 2024; Aromaa et al., 2025; Toorajipour et al., 2024). The truth is that a lot of organizations own little data that is incomplete or unstructured (Haridasan et al., 2024) while also adding to a lack of knowledge about how to manage and how to make it safe for GenAI systems (Barrenechea et al., 2019; Davenport, 2018). As authors (Abraham et al., 2019) state, an organization without data governance "spends more time reacting to data-quality issues, which in turn limits the time spent on running the business and making processes improvements". Data needs to be "clean, consistent, and well-integrated throughout the organization" (Davenport, 2018) and aligned with principles and policies (Susan Earley et al., 2017), which leads to this requirement of an initial definition of current needs, resources, measures and practices. Similarly, awareness valuation relates to the organization's consciousness about its present condition and all the mentioned factors — without proper awareness of what is happening and what is desirable, organizations will have a hard time functioning with such technologies.

Therefore, the "*Organization Strategic Definition*" level is the preparation, a pre-adoption phase of GenAI, focused on aligning the technology with organizational needs and envisioning its role in improving, particularly, knowledge management processes. In all levels of the framework, connections exist to comprehend how they relate to the other elements as supporters or enablers. In this case, Information Management is depicted as a guiding force for organizational strategy definition. The activities that are inside the IM box are common and known contributions of this discipline in organizational context; it is, indeed, a complement or extension of the first level, as without information management this strategic definition would not be possible. As author (C. W. Choo, 1996) expresses, "an organization uses information strategically in three areas: to make sense of the change in its environment; to create new knowledge for innovation; and to make decisions about courses of action", while also adding that an intelligent organization is prepared with skills to manage information resources and capabilities, transforming into knowledge to create decisions that are relevant for the organization. Furthermore, (Rowley, 1998) refers to IM as a way to "promote organizational effectiveness by enhancing the capabilities of the organization to cope with demands of its internal and external environments in dynamic as well as stable conditions". Therefore, IM is essential in all aspects of the organization and supports its decisions and changes. In the framework, it is possible to visualize the connection where IM acts as a primary force that manages "Data, Information and Content Lifecycles".

Based on the literature review and the knowledge acquired from its exploration, the activities introduced in the IM box are considered applicable to the context of GenAI integration and its impact on KM processes. For instance, understanding organizational and customers needs is directly tied to identifying business needs. Information managers play a vital role in interpreting and responding to organizational and market demands (Wilson, 2011). With such understanding, organizations can strategically determine where GenAI should be applied, what data/information is necessary to feed the model, and how it aligns with business needs. Simultaneously, identifying data and information remains critical, as it deals with the "information explosion" mentioned by (Rowley, 1998), which controls, analyzes, and synthesizes information for decision-making activities.

What data and information is necessary for the thinking of organizational strategy which embarks the integration of GenAI technology as a way to improve knowledge management processes and, consequently, also improve organizational success and performance? The preoccupation to enable this is a core aspect of information management that enables the organization to learn and adapt. Furthermore, the IM role is extended to activities such as the location and gathering of useful data and information. One hugest concern for IM is that a lot of valuable information and knowledge within the organization remains scattered, unorganized, hidden, or effectively invisible to the ones that need it. It is particularly pertinent that available data and information is properly interpreted, assuring that quality, and overall value of data and information are considered. Furthermore, IM ensures that stored information is easily retrievable and accessible when necessary, enabled by the identification of proper metadata (Chun Wei Choo, 2002). If the information is easily organized and retrievable, then it automatically facilitates the elaboration of the organizational strategy within the context of a GenAI adoption, as the organization can join the pieces that support this analysis. Still considering information retrieval, the organization of information as an IM management process enables indexing, categorization, and classification of information (Detlor, 2010; Chun Wei Choo, 2002). The transformational aspect of this technological evolution is, that not only information management participates in the good development of GenAI with these well-known processes (creation, acquisition, organization, storage, distribution, and use (Detlor, 2010)), but it can be greatly improved by GenAI tools, automatizing some of the tasks and processes. As users use prompts to communicate with GenAI in natural language (Teubner et al., 2023; Alavi; D. Leidner, et al., 2024; Böhm et al., 2025), facilitating the communication between human workers and technology (Aromaa et al., 2025), it is possible to retrieve information from documents, making human workers spend less time looking for and retrieving information that is necessary for a task and decision (Holmström et al., 2024; Kaczorowska-Spychalska et al., 2024). Authors (Kaczorowska-Spychalska et al., 2024) adds that GenAI can "facilitate knowledge capture by automatically extracting relevant information from various sources, such as documents, emails, or audio recordings", while (Taiwo et al., 2024) conducted a study about information retrieval and knowledge discovery that states how GenAI can query contract documents with details and requirements that are too complex for manual searching. Therefore, this synergy between GenAI and IM is represented by a relationship in which IM manage the entire information lifecycle that contributes to the adoption of GenAI, while GenAI automates and assists several tasks from IM.

As organizations initiate these discussions and gain awareness on how to take advantage of the discipline while understanding the impact of GenAI on it, it seems that more opportunities to enhance their processes grows. Following the hierarchical data–information–knowledge structure, IM serves as an enabler for KM by transforming information into knowledge enriched with experience, values, and expertise (Rowley, 2007; McInerney, 2002; Payne et al., 2020; Blair, 2002).

Together, these insights provide a basis for organizations to comprehend how IM and KM interrelate, how they are influenced by GenAI, and how to strategically employ these disciplines to advance GenAI adoption. A more comprehensive and deep research is necessary to understand how IM and GenAI interact with each other and leverage organizations to their full potential.

5.2.2 Data and Ethical Preparation Level

The "*Data and Ethical Preparation*" level builds upon the "Organizational Strategic Definition" and the "Data, Information and Content Lifecycles" managed by IM. At this stage, GenAI starts to be considered in a direct and explicit way. GenAI relies on data to generate outputs and this data needs to follow a certain criteria, involving the introduction of data management and governance strategies and practices. In parallel, author (Davenport, 2018) mentions how "automated or semi-automated technologies can aid the process of cataloging data, keeping track of data provenance, and enforcing data governance rules". Once again, it is clear how this technology is impacted and impacts other enabling disciplines.

This level is particularly critical in contemporary contexts, as organizations face significant data-related problems and challenges in implementing GenAI solutions (Haridasan et al., 2024; Q. Zhang et al., 2025). These challenges include data availability, quality, privacy, security, and ethical concerns about the data that organizations hold and feed GenAI models, which are trained and operate through this data (Haridasan et al., 2024; Taeihagh, 2025). Organizations possess several data quality problems, where an absence of necessary technology and processes to fix it is notorious. Moreover, data often originates from various sources such as independent business units and functions, but also because collaboration exists between other organizations that hold different databases or data architectures. It is, indeed, a very time consuming and labor intensive task to take care of the available data dispersed in different technologies while also having problems with its quality and quantity. (Davenport, 2018).

After a thorough evaluation of available resources and conditions such as data readiness, financial resources, technological infrastructure, and business needs evaluation, organizations face a demanding and rigorous challenge to create a data management and governance strategy.

The framework presents Data Governance and Data Management connected with "Data, Information and Content Lifecycles". DG concern is about oversight — it ensures that the right rules, policies, standards, and controls are in place so data is used responsibly and ethically. DM focuses on execution — it involves the practical activities of acquiring, storing, protecting, and using data to meet organizational goals (Susan Earley et al., 2017). Both retain specific purposes, needing to work together to achieve an optimization for data.

Starting with data governance, some measures need to be considered when thinking about using the organizational data to develop GenAI. How DG will be implemented depends entirely on organizational needs (Susan Earley et al., 2017), which were discussed and defined in the below level. As author (Abraham et al., 2019) argues, data governance "enables collaboration across functional boundaries and data subject areas", it is a framework that provides "structure and formalization for the management of data", and, finally, "it focuses on data as a strategic enterprise asset". As a result, following a robust data governance strategy, it ensures that data utilized in GenAI models is "reliable, timely, relevant, accurate" (Attard et al., 2018), and has a good potential to generate positive and effective benefits for the organization that desires to leverage KM processes.

Based on (Susan Earley et al., 2017), specific measures were selected to define the most important actions required for an effective DG strategy. By establishing data policies and data standards, an organization can provide "high-level guidelines and rules regarding the creation, acquisition, storage, security, quality, and permissible use of data". These policies are used to communicate "key objectives, data accountabilities, roles, responsibilities, and data retention periods". While data standards, defined internally by data stewards, data architects or by external organizations, ensure that "data representation and the execution of data-related activities are consistent and normalized throughout the organization (Abraham et al., 2019; Susan Earley et al., 2017). For GenAI, which relies on extensive and high-quality training datasets to generate accurate results (Shafiee, 2025; Q. Zhang et al., 2025), policies and standards are paramount to ensure these datasets are "representative, diverse, and free from biases" (Jin et al., 2024).

Authors (W. Zhang et al., 2025) emphasizes the importance of establishing data quality control standards and governance strategies for GenAI to address data-related ethical issues, making sure that procedures such as "updating, auditing, verifying, and evaluating databases" are taken seriously. This leads to measures that ensure that organizations are complying with these policies, standards, and procedures. As the author (Abraham et al., 2019) mentions, compliance monitoring is needed to track and enforce organizations to follow regulatory requirements. As a matter of fact, mentioning an example of AI regulation in the European Union, there is the framework "EU's AI act" and the GDPR (General Data Protection Regulation) that directly impacts how these technologies must operate and how data is handled (Dwivedi; Hughes, et al., 2021; Dwivedi; Kshetri, et al., 2023).

Regarding transparency and explainability requirements, these are crucial for organizations to build trust in the GenAI system, addressing the "black box" nature of these models (Liang et al., 2023; Banh et al., 2023), thereby enabling human workers to trust and understand the processes and decisions derived from this technology. Attention to these aspects reduces risks that can potentially impact people and society, since GenAI is intended to aid decisions that involve high levels of responsibility (Banh et al., 2023). Thus, organizations must be able to explain how GenAI systems are generating a specific output, how they make decisions (Kellogg et al., 2025; Davenport, 2018). Failures in this area, from data bias to hallucinations, can compromise the whole company, leading to wasted resources (Q. Zhang et al., 2025), increased operational costs (Rajaram et al., 2024), market disruption (B. Andres et al., 2025), loss of credibility and trust (Ramaul et al., 2024), and many other problems. Having all these problems at sight, accountability needs to be assigned clearly, defining who holds decisions right and who is responsible for decisions regarding data assets (Abraham et al., 2019). Nonetheless, assigning accountability for GenAI decisions remains challenging due to the complexity of these technologies (Janssen, 2025). These measures contribute to reducing negative societal impacts, but there is a huge necessity to think clearly and strategically about the GenAI's characteristics, the companies needs and interests to ensure that an adoption of this technology is fluid and unproblematic. To that end, risk mitigation strategies and privacy protections must be enacted to safeguard data from "falsification, destruction, and unauthorized disclosure"(Engels, 2019).

Having addressed considerations about data governance, it is indispensable to mention the organization's necessity to apply data management to ensure that data is effectively handled throughout its lifecycle to achieve organizational goals (Susan Earley et al., 2017; Permana et al., 2018). The conceptual models presented in the section 4.3 of data management and data governance acted as tools to comprehend each domain and what actions are required to address common and persistent challenges related to data quality and other related aspects, such as the architecture, storage, and metatadata management (Susan Earley et al., 2017). As (Doanh et al., 2023) affirms, AI's effectiveness in quality control is fully dependent on the quality and diversity of the data it is trained on. Similarly, (Z. Zhang et al., 2025) also notices that it is necessary to resolve privacy concerns associated with unfiltered data, leading to "the creation of comprehensive high-quality training datasets becomes crucial for effectively training high-quality GAI models".

For instance, GenAI also offers the capability to enhance data quality and consistency. Author (M. Ghobakhloo et al., 2024) presents ways on how GenAI impacts data quality when a model is already implemented. As an example, "it aids in data augmentation by generating synthetic data and diversifying datasets for better model training". This technology also contributes to anomaly detection, identification of outliers, and maintains data consistent. Furthermore, it facilitates data cleaning and imputation by "predicting missing values, leading to improved dataset integrity". However, this is applied when models are integrated and prepared to develop these tasks, assuming that they are able to support and enhance data quality challenges such as those. That is not the norm for most companies that are interested in applying GenAI to their business processes, since data availability and quality is a common issue that plagues companies (Davenport, 2018). Therefore, this framework presents some of the measures that need to be applied to contribute to the effective use of the GenAI system that will impact and improve knowledge management processes — the focus of this dissertation. Data management encompasses the certainty that data is managed to be prepared for its use, attending quality issues, its accuracy, uniqueness, validity, completeness, and reliability (Susan Earley et al., 2017). In the context of GenAI, training models considering these data characteristics is paramount to produce reliable results that are also trustworthiness — it prevents that organizations make wrong decisions related to poor data (Doanh et al., 2023; Q. Zhang et al., 2025). Decisions about data architecture definition, metadata management, and the continuous improvement of its integration and interoperability are part of the role of data management.

For the future of this research, there's an intention to develop stronger data management and data governance insights associated with the use of GenAI in organizational and other contexts, recognizing the inherent complexity and extensiveness of this subject. However, the most important output of this framework is sustained by GenAI as a technology that relies on data quality to function, while DM and DG supports this with practices that offer some safety to advance and ameliorate processes.

5.2.3 GenAI System in a Sociotechnical Context Level

The middle level of this framework concerns the GenAI system itself, integrating it with a sociotechnical view — the interplay between the social and technical system. The idea behind the introduction of this theory is based on i5.0 values, specifically human-centricity, that aims to go beyond technology alone but integrate human and social aspects to create an optimization of both sides (Akbarighatar et al., 2023; Makarius et al., 2020). GenAI is inherently a technology composed of social and technical components (Akbarighatar et al., 2023).

This artifact does not aim to provide an exhaustive treatment of GenAI from a sociotechnical systems perspective, but seeks to offer a meaningful contribution that may be explored further. This approach is essential for GenAI adoption because it fosters a comprehensive understanding of the intricate interaction between technology and human-organizational elements, which is crucial to maximize benefits and mitigate potential risks such as societal ones (Akbarighatar et al., 2023; Govers et al., 2019; Yu et al., 2022). As a matter of fact, most researches about GenAI are mostly technocentric, lacking or under-emphasizing social, ethical, and human impacts (Akbarighatar et al., 2023; Janssen, 2025). Although technical aspects are indispensable for GenAI to function properly, it cannot produce results that are satisfactory if it is not aligned with humans and business needs (Makarius et al., 2020). By addressing social aspects, organizations can predict and mitigate risks associated with the adoption of these technologies (Davenport, 2018). For this reason, the following social aspects were considered for the social system of the applied STS theory as the GenAI system operating within it: Human cognitive capabilities; workers roles, skills and responsibilities; creativity and knowledge creation; organizational communication and knowledge sharing; human-GenAI trust; collaboration worker-GenAI; and organizational performance. GenAI impacts directly human cognitive capabilities with its ability to emulate human cognitive capabilities and interact just like a human through its natural language processing (NLP) ability (Makarius et al., 2020; Kumar et al., 2025). Furthermore, GenAI is able to adapt to the context of the user, by "sensing the environment, learning from experience, and creating possibilities for actions tailored to specific tasks" (W. Zhang et al., 2025). These capabilities are mentioned in the "*GenAI System*" - "*Capabilities*", as the most general and relevant capabilities to interact with the other elements of the framework. "Cognitive emulation" and "human-like interaction" on the left side, corresponding to the social system side while "generative multimodal output" (referring to the capacity of GenAI to generate and convert outputs in different formats and types) (Akhtar et al., 2024; Banh et al., 2023)) and contextual adaptability placed on the right side relating to the technological system part.

Generative AI supports workers routines by collaborating with them, by performing specific tasks that traditionally required human intelligence while also supporting a rapid decision-making process (Schecter et al., 2025). It is capable of improving creation and knowledge creation, as its multimodal characteristic can generate insights, innovative, and creative ideas (Potthoff et al., 2024). All these possibilities are seen as potential benefits for organizational performance, while it increases productivity, quality of knowledge work, and innovation such as the creation of new products (Hai et al., 2025; Aunimo et al., 2023).

Nevertheless, workers are also concerned about the roles, skills, and responsibilities they might need to remain competitive and collaborate with GenAI (Hai et al., 2025; Rajaram et al., 2024; Q. Zhang et al., 2025). Due to the deployment of GenAI, workers must develop their cognitive skills, such as the capacity to learn, be creative, innovative, analytical, and critical thinking necessary to align with the outputs generated by the technology (Bankins et al., 2024). Soft skills are now even more valuable, as empathy, active listening, and collaboration is crucial for workers to have a distinctive factor in the current technological evolution (Grybauskas, 2024). Simultaneously, workers' responsibility and accountability is also changing. They must be aware of the ethical issues related to AI, which can be achieved through training programs, knowledge sharing, and collaboration (Akbarighatar et al., 2023). In this aspect, the "*Human-feedback loop*" is introduced between the social system and the GenAI system. According to (Riemer et al., 2024), "the exploration of different emerging human-in-the-loop approaches, or human AI work configurations will be part of the research agenda", since the autonomous part of these cognitive and intelligence technologies demands humans to control it and make decisions about it. From a technical system perspective, encompassing both technological and task-related dimensions, this framework illustrates the integration and operational context of the GenAI system. The constituent elements of this system are specifically aligned with the dissertation's objectives, establishing a clear link to their influence on processes, such as knowledge management, which will be explored in the next level "*Knowledge Management (KM) Processes Enhanced by GenAI*".

In regards to the Knowledge Management Systems (KMS), a class of IT-based information systems designed to support and enhance organizational knowledge processes (Alavi; D. E. Leidner, 2001), can be greatly influenced by the emergence of Generative AI (Alavi; D. Leidner, et al., 2024). As this dissertation encapsulates, GenAI impacts knowledge management processes (creation, storage and retrieval, transfer and sharing, and application) in different and unique ways. For instance, users can query the KMS in natural language, making retrieval more intuitive and reducing barriers for non-technical users or even a more semantic search, which is facilitated by GenAI's ability to understand the context and intent of the user, delivering more interesting and relevant results. It also optimizes KMS by the ability to storage and retrieve unstructured data (Alavi; D. Leidner, et al., 2024). The technical system also includes the same elements discussed above in relation to data management and data governance, since the appropriateness of data directly impacts the quality of decisions made as a response of GenAI's on knowledge management processes (Taherdoost et al., 2023). Ethical considerations and data quality and availability are essential elements of the technical system which GenAI is related.

5.2.4 Knowledge Management Processes Enhanced by GenAI Level

Considering the framework described thus far, it becomes evident that these preceding steps are essential for GenAI to influence knowledge management processes in a way that delivers results and supports organizational growth and success (Kumar et al., 2025; Kanbach et al., 2024). Once the GenAI system is properly prepared and integrated into business processes, the next relationship outlined in the framework involves the impact of this technology on KM processes — this is represented by the level titled "*Knowledge Management (KM) Processes Enhanced by GenAI*.

At this level, one can observe each knowledge management process and some of the impacts that Generative AI can potentially exert on them. Each corresponding element in the framework box highlights specific activities identified through an extensive literature review and ongoing examination of emerging developments in the field. These impacts are social and technological in nature and are represented by the connection between this level, the "Social System" and "Technical System" with the linking words "part of". As the literature review of this dissertation addresses each knowledge management process and the respective GenAI's impact, this description will be mostly superficial, indicating some of the impacts as a representation of the artifact.

The integration of GenAI into KM introduces a significant shift in the way organizations conceptualize and execute core knowledge processes. By augmenting human cognitive limitations and enabling new modes of knowledge creation, storage and retrieval, transfer and sharing, and application, GenAI becomes a transformative driver of KM evolution.

In the *Knowledge Creation* process, GenAI is suitable for enhancing the process by augmenting human cognitive capabilities, while compensating for limitations in memory, attention, and processing speed (Alavi; D. Leidner, et al., 2024; Leoni et al., 2024). As (Krakowski, 2025) explains, "AI refers to machine agents that "perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" in pursuit of goals. This impact directly facilitates workers' information processing and cognitive functions, with important implications for both individual and collective learning (Alavi; D. Leidner, et al., 2024; Krakowski, 2025). By extracting and summarizing large volumes of information, GenAI empowers users to easily synthesize and recombine existing knowledge, thereby facilitating the combination and internalization stages of the SECI model (Ikujiro Nonaka; Takeuchi, 1995; Alavi; D. E. Leidner, 2001; Alavi; D. Leidner, et al., 2024). A significant benefit of augmenting human cognitive capabilities lies in its potential to improve the well-being of the worker through the reduction of cognitive overload, enabling new approaches to more complex and strategic cognitive tasks (Aromaa et al., 2025; Holmström et al., 2024; Potthoff et al., 2024). GenAI also offers opportunities to automate repetitive and tedious tasks, which are often part of the daily work routines (Q. Zhang et al., 2025).

Nonetheless, as workers gain more time to focus on creative problem-solving tasks (Holmström et al., 2024), they can also utilize GenAI to amplify their creativity capabilities by generating insights, as this technology excels at "generating new content, identifying patterns, and making predictions" (Alavi; D. Leidner, et al., 2024). Giving a concrete example, (Potthoff et al., 2024) expresses how GenAI facilitates human designers by producing new and creative ideas. While GenAI offers beneficial impacts for product design and personalization in the manufacturing industry, (Akhtar et al., 2024) argue that further research is needed to support sustainability and circular economy goals.

The multimodal capabilities of GenAI enable the generation of content in diverse formats and styles, thus reinforcing the creative and innovative dimensions of knowledge creation (Feuerriegel et al., 2024; Banh et al., 2023). Concurrently, GenAI accelerates research and discovery by creating synthetic data and simulations that allow researchers to explore scenarios that would be impractical or impossible in physical settings (Krakowski, 2025). Furthermore, by creating scenarios, GenAI can generate personalized learning experiences for workers across various expertise levels, skills sets, and technologies, adapting dynamically to users' contextual needs (Potthoff et al., 2024).

Regarding the *Knowledge Storage and Retrieval* process, critical to "create and maintain an organizational memory that tracks generated and acquired resources" (Jarrahi et al., 2023), the impacts of GenAI are primarily associated with managing stored knowledge and and facilitating efficient, rapid retrieval. Organizational memory consists of both semantic (explicit) and episodic (context-specific) memory, which must be managed and codified, as it contributes to organizational learning and decision-making (Alavi; D. E. Leidner, 2001). This process ensures that knowledge is accessible throughout the organization, enabling and influencing processes such as knowledge transfer and sharing (Grover et al., 2001). This framework elaborates some of the impacts that GenAI can have in the knowledge storage and retrieval processes.

For instance, GenAI significantly improves knowledge accessibility by enabling workers to efficiently retrieve relevant information from diverse sources. This makes it simpler to find only the relevant data and information needed for decision-making and simultaneously reduces information overload, as workers spend less time searching for it (Alavi; D. Leidner, et al., 2024; Q. Zhang et al., 2025; H.-P. (Lee et al., 2025). Additionally, author (Kaczorowska-Spychalska et al., 2024) highlights that GenAI facilitates the discovery of hidden knowledge by analyzing data from different sources and drawing connections between them, thereby uncovering new insights.

Another important contribution of GenAI on the knowledge storage and retrieval process is the ability to automate tagging, categorization, classification, and indexing, which are essential to improve organization and processing of information and knowledge assets (Kaczorowska-Spychalska et al., 2024; Jarrahi et al., 2023; Q. Zhang et al., 2025). Authors (Kaczorowska-Spychalska et al., 2024) affirm that GenAI capabilities can enhance the organization for storage and retrieval since it can rapidly analyze content, identify keywords, and allocate proper metadata. This assures that workers can easily retrieve knowledge that they need at the right time. Concurrently, this technology "enables navigation and understanding of knowledge assets", since it can combine similar information from various stored sources, identify the relationship between those knowledge assets, and suggest taxonomies and ontologies (Kaczorowska-Spychalska et al., 2024). As a result, it can generate knowledge graphs, knowledge maps, and other visualization methods from unstructured text, supporting workers in the comprehension of knowledge assets within the organization (Kaczorowska-Spychalska et al., 2024; C. Zhang et al., 2025). For example, in the manufacturing industry, there is a problem related to the isolation and inconsistency of data systems, which can be ameliorated by generating knowledge graphs that offer workers "contextual understanding and increases data-driven decision making" (Escobar et al., 2025).

These interactions are enabled by GenAI's capacity to comprehend and generative content in natural language, enhancing the effectiveness of human-machine collaboration in information and knowledge retrieval (Böhm et al., 2025; Li et al., 2024). Authors (Jarrahi et al., 2023) offer an example of how GenAI improves the storage and retrieval of explicit knowledge, as it can "analyze multiple channels of content and communication, generate summaries, ascertain relevant topics (to emerging problems), isolate proprietary and confidential knowledge, and present reusable insights that are immediately applicable to new situations". Having these potential changes in the process of storing and retrieving knowledge is essential for organizations to apply knowledge in their processes, since workers do not need to deal with extensive and tiresome work of analyzing and finding what is necessary to support an important decision that will impact the business.

In the following knowledge management process, "*Knowledge Transfer and Sharing*" is a critical key process that enables other KM processes as "knowledge has limited value if it is not shared" (Lai et al., 2000). When knowledge is effectively transferred and shared, organizations gain the ability to integrate and apply this specific relevant knowledge across the organization and processes, which can strengthen competitive advantage (Grant, 1996; Lai et al., 2000).

One challenge that devastates effective knowledge sharing is how, in many organizations, sharing knowledge is local and fragmented (Jarrahi et al., 2023). In this case, GenAI is capable of breaking organizational silos by facilitating the collaboration of workers that are separated and distanced, as they can be from different countries and speak different languages (Jarrahi et al., 2023; Taherdoost et al., 2023). These challenges are addressed by GenAI's capabilities of "composing text bodies, summarising more extensive and descriptive data, instant translation of different languages, creating codes for auto-completion, and creating images, technical drawings, logos and icons" (Modgil et al., 2025). These outputs offer new modes for workers to transfer and share knowledge in different formats and styles, tailored to the needs and preferences of diverse users. As a result, GenAI not only breaks down information silos but also enhances virtual collaboration.

Collaboration is further improved by "facilitating communication across multiple information channels", promoting the transfer of tacit knowledge that fosters "a more dynamic exchange between individuals". Why is this important? Tacit knowledge is notoriously challenging to codify due to its "intuitive, sensory, emotional, and situational characteristics". Workers have a harder time to communicate, share, and transfer tacit knowledge from all the experiences and expertise they've gained over the years. As a result, GenAI has the ability to contribute to this codification, transforming tacit knowledge through features such as "voice, facial recognition, and gestures" into explicit forms that are easier to understand and internalize (W. Zhang et al., 2025).

A crucial impact of GenAI in the knowledge transfer and sharing process is how it enables personalization learning and recommendation for workers. Knowledge storage and retrieval enable many knowledge sharing processes, as it makes information and knowledge accessible to workers. Here, GenAI contributes to the dissemination of knowledge by providing workers with personalized content and recommendations, shaped to their context and needs (Kaczorowska-Spychalska et al., 2024). In both organizational and industrial contexts, the arriving of new employees can be facilitated in terms of knowledge sharing. GenAI analyzes employee roles, characteristics, and expertise, responding and tailoring knowledge in formats that are helpful and engaging. These personalized options improve knowledge transfer through the generation of interactive tutorials and simulations, integrating new workers into the organization (Alavi; D. Leidner, et al., 2024). This will also contribute to the knowledge application process.

In manufacturing contexts, authors (Morteza Ghobakhloo et al., 2023) specifically mention the impact of GenAI in knowledge transfer, aligning with i5.0 sustainability goals. The "advanced training and knowledge transfer (ATK)", specified in the article, mentions how GenAI is capable of upskilling and reskilling less experienced workers through tailored guidance to their necessities, aiding workers to easily manage complex production companies. This leads to a reduction of time and resources that would be traditionally necessary to train an operator. Specific and tailored transfer of knowledge contributes to an enhanced collaborative environment, where knowledge workers of different backgrounds and expertise can be empowered and aligned. The authors (Q. Zhang et al., 2025) have expressed that GenAI analyzes user preferences and behavior to guide workers with personalized information, which enhances efficient knowledge transfer. Furthermore, the democratization of knowledge access is utterly relevant. as GenAI can enhance knowledge sharing between workers of different expertise, deconstructing knowledge hierarchies by making "specialized expertise more widely accessible to employees" (Benbya; Deakin University, et al., 2024; Shi et al., 2024). In terms of upskilling and reskilling authors, GenAI focus on the unique characteristics and context of the workers, providing knowledge through guidance to less experienced operators and assists them in managing complex production companies through the creation of personalized tutors (M. Ghobakhloo et al., 2024).

By equipping workers with skills needed to perform certain tasks more effectively, it is possible to advance to the next knowledge process, "*Knowledge Application*", since it enables them to make more informed and accurate decisions with learned and acquired knowledge (Benbya; Deakin University, et al., 2024). GenAI supports decision-making across all levels of expertise. For instance, it assists novice financial analyst workers in making "accurate predictions and provide insightful recommendations" (Brynjolfsson et al., 2023; Benbya; Deakin University, et al., 2024). Therefore, personalized learning and skills acquisition are not only central to knowledge transfer and sharing process, but also for effective knowledge application — it empowers employees to apply knowledge more confidently and competently in organizational decisions.

As an example, GenAI enhances knowledge application by generating scenarios and alternative solutions grounded in existing knowledge, thus ameliorating the decision-making process (Kaczorowska-Spychalska et al., 2024). Leveraging natural language processing (NLP) and advanced data analysis capabilities, GenAI enables more accurate and sometimes automated decision-making. The predictive mode of GenAI can aid businesses by predicting and generating insights for "forecast market trends, changes in customer demand, or potential risks" — it extracts meaning from structured and unstructured data, which is essentially knowledge to be applied (C. Zhang et al., 2025). Although, since GenAI contributes with outputs such as summaries from different sources that informs workers of the essential content to utilize for a decision making process, it is important to mention that humans are still in charge of the decision through their critical thinking, based on or not on the outputs generated by GenAI (H.-P. (Lee et al., 2025; C. Zhang et al., 2025).

In the manufacturing industry, (M. Ghobakhloo et al., 2024) exemplifies how GenAI minimizes human errors "by providing instantaneous data insights, fostering a more informed decision-making process", allowing workers to focus on more complex tasks, interpret and leverage information essential for decision-making efficiency within shop-floor processes. This relates to operational efficiency by aiding and augmenting human cognitive capabilities. Lastly, in simulation and predictive capabilities, GenAI generates and predicts improvements, streamlines production processes, and discover problems and challenges that might be related to production processes (Shafiee, 2025).

Overall, the integration of GenAI into knowledge management processes introduces significant enhancements across creation, storage and retrieval, transfer and sharing, and application. By augmenting cognitive functions, enabling personalization, and improving accessibility, GenAI transforms how knowledge is generated, disseminated, and utilized within organizations and industry. These advancements support more efficient, collaborative, and informed knowledge pratices, reinforcing GenAI's role as a key enabler of organizational learning and strategic decision-making.

5.2.5 Organizational Expected Results Level

Finally, the last level of this framework is the "*Organizational Expected Results*", which corresponds to the outcomes that organizations can expect to achieve by successfully implementing all preceding steps and realizing the impact of GenAI on knowledge management (KM) processes. The literature on the adoption and application of GenAI indicates that organizations can optimize performance and value creation by significantly increasing productivity, allowing employees to work smarter rather than harder, resulting in more time for other tasks (Akhtar et al., 2024; Feuerriegel et al., 2024). For example, in the manufacturing industry, GenAI can leverage processes in a way that reduces waste and costs, leading to the creation of value while aligning to the sustainability values of Industry 5.0 (M. Ghobakhloo et al., 2024). This realization also leads to the "Sustainable and Resilient Organizational Growth", where manufacturers can use GenAI to help them "develop eco-friendly products and processes that enhance resource efficiency and minimize environmental impact" (M. Ghobakhloo et al., 2024). The same author states that GenAI improves shop-floor decision-making efficiency "by automating routine tasks and facilitating streamlined data accessibility, ensuring that human operators can efficiently interpret and leverage information".

The most important insight from this dissertation comes from the exploration of how knowledge management has evident implications for organizational performance (Alavi; D. E. Leidner, 2001). In fact, managing knowledge effectively contributes to the achievement of a competitive advantage, which is supported by the Knowledge-Based View (KBV) theory of the firm (Grant, 1996; G. Liu et al., 2022; Ikujiro Nonaka; Takeuchi, 1995). Therefore, companies can anticipate better outcomes, such as a competitive edge, if there is a system like GenAI that quickly leverages knowledge and improves knowledge management processes (Alavi; D. Leidner, et al., 2024; Kaczorowska-Spychalska et al., 2024). By analyzing and extracting insights from extensive datasets, organizations can improve the precision of management decisions by storing, transforming data, information, and knowledge (C. Zhang et al., 2025; Leoni et al., 2024). Authors (Leoni et al., 2024) notes that the adoption of GenAI within KM processes makes workers more informed of the decisions they want to follow, as the exchange of information is rapid. As a result, employees can quickly and efficiently access relevant information and knowledge, enhancing decision-making while also asking for insights and scenarios that help them to support problem-solving (Alavi; D. Leidner, et al., 2024; Ma et al., 2024).

With respect to "Human-Centric Workforce Empowerment", GenAI empowers workers by enabling knowledge creation, stimulating creativity, supporting learning, and fostering innovation (Krakowski, 2025). It helps them to visualize and comprehend hidden patterns, both from structured and unstructured data, which human cognitive abilities would seldom acknowledge (Shi et al., 2024). Moreover, as organizations hold workers with different levels of expertise, GenAI can contribute with personalized and contextual learning, improving the "progression from novice to expert, while freeing up time and resources for other work" (Storey, 2025).

In summary, the "Organizational Expected Results" level demonstrates how GenAI enhances decision-making, empowers workers, and supports sustainable value creation through improved knowledge processes. Especially within manufacturing, these benefits underscore GenAI's potential to boost productivity, reduce waste, and foster human-centric innovation, positioning organizations for more adaptive and resilient growth.

5.3 Evaluation and Validation of the GAKMF Framework

The evaluation and first iteration of this framework was developed through the execution of a focus group session with experts from different areas associated with the framework: information management, knowledge management, data management, data governance, and GenAI. The session included four participants: three attended in person, and one joined remotely. All these participants have backgrounds and expertise related to each discipline and level of this framework — from information/knowledge management, data management and governance, and Generative AI. This diversification of expertise and backgrounds was essential for gaining a broader perspective on the framework's evaluation and validation.

Prior to the session, participants were provided with the focus group session document through email to support their preparation and to ensure familiarity with the relevant aspects of the framework. This preparatory step allowed participants to grasp both the overall scope and intricate details of the framework.

During the recorded session, participants were first introduced to the foundational rules and objectives of the session. This was followed by a detailed presentation and contextualization of the framework, in which its structure, decisions, and purposes were thoroughly explained. After this orientation, participants engaged in a guided discussion based on a series of questions designed

Table 5.1: Summary Table of the Generative AI-Enhanced Knowledge Management Framework (GAKMF)

Framework Level	**Core Functions and Activities**	**Supporting Disciplines**	**GenAI Contributions**	**KM Processes Impacted**
Organization Strategic Definition	Identify business needs, assess data and information resources, evaluate readiness and strategy	Information Management (IM)	Guides strategic GenAI use through goal alignment and information analysis	All KM processes via strategic alignment
Data and Ethical Preparation	Define data policies, ensure data quality, oversee compliance, ethical risks, and accountability	Data Governance (DG), Data Management (DM)	Ensures quality, ethics, and compliance of GenAI training data and output	Indirect support for all KM processes
GenAI System in Sociotechnical Context	Coordinate human-AI feedback loop, embed GenAI in technical and social structures	Sociotechnical Systems Theory (STS)	Operates within the Social and Technical System, impacting social and technical aspects	Knowledge Creation, Transfer, Application
KM Processes Enhanced by GenAI	Create, store, retrieve, transfer, and apply knowledge in augmented ways	Knowledge Management (KM) theory (Alavi & Leidner)	Automates tasks, augments creativity, personalizes content, supports decision-making	Direct impact on all KM processes
Organizational Expected Results	Improve performance, enable innovation, empower workers, support sustainability	KM + GenAI integration across layers	Informs strategic agility, enhances decision-making, enables human-centric design	Outputs and benefits from improved KM processes

to evaluate each level of the framework. The questions used during the session are presented in Appendix A).

To facilitate the presentation of the evaluation and validation, they are divided into the following sections:

5.3.1 Perception, Comprehensibility, and Target Audience Feedback

The initial questions pertained to the framework's structure. From this preliminary perspective, participants were asked if the framework's narrative — including its relationships and interacting disciplines — was clear and comprehensible. It was important to grasp the first impressions; if all aspects in context were taking into consideration.

The participants provided several observations on the structure and presentation of the framework. A common opinion was that the framework was quite complex and text-heavy. If the framework was to be presented to executives or organizations, *participant 00* said "I think, from that perspective, if these were for company executives who were responsible for this part of the integration (...), I think it is too complex. I don't think the initial presentation format should be exactly this framework. I am talking more about the format than the content. (...) for an executive, it would need to be a more summarized, a more introductory version of each box." However, *participant 04* mentions how important it is to define the initial target for whom this framework is created for, "(...) for a company, this is too complex. Firstly, because many companies don't even know what processes are. Therefore, I also think it is important that you define well the type of target, as many of these questions then have different discussion perspectives. In other words, it is still complex, (...) because it has a lot of text. But I also understand why it is like this. Despite its extensiveness, a researcher who intends to take this to do some work on this, I think the diagram itself is perceptible. I think it is explained". Adding to the discussion of what the target is and who informs how the framework is constructed, *participant 01* argues that "I see this framework as very broad and very complete, (...) for other researchers to take the framework and deepen the work". This participant mentions how it can be applied and further changed to what other researchers intend to explore in their research — they can be interested in a specific knowledge management process and focus only on the impacts of the GenAI on that process. Additionally, the direction of the framework was also mentioned by *participant 01* "(...) a person looks at the diagram and it is a bit complicated at first glance to read it, (...) it is from bottom to top. Normally we are used to having it from top to bottom, that is, a direction for the reader to know to proceed". Moreover, *participant 04* reiterates that it is paramount to define objectives and the target of the framework by saying "(...) instead of offering a structured model to help organizations leverage AI, change to offering a structured model to help consultants, practitioners in this area to help organizations leverage AI. Your results allow, for example, a consulting service (...) to work on what is relevant. There are two interesting things: one is someone taking this and now trying to gather data beyond the literature, and therefore we are talking about only one target, which is a researcher, (...) or even a practitioner from the point of view of a consulting service who wants to help organizations and who also uses this as a basis for their work."

This feedback highlights the importance of defining the framework's target audience. While its comprehensiveness and detail were acknowledged as strengths, particularly for academic and research contexts, the participants highlighted the need for adaptation and simplification when targeting organizations and organizational leaders. The feedback suggests that future iterations could benefit from multiple versions or layers of the framework, tailored to specific audiences such as researchers, consultants, and business executives. This differentiation would enhance its usability and applicability, ensuring that the framework not only informs the academic environment but also serves as a practical tool for guiding GenAI implementation in diverse organizational contexts.

5.3.2 Structure and Visual Representation Feedback

To understand the connections in the framework, participants were prompted to analyze concrete relationships. The first question specifically addressed the "supports" connection linking "Organization Strategic Definition" with "GenAI System", asking participants to assess its relevance. The overall consensus was that this connection was not useful and purposeful, since it is already implicit in the relationship that supports "Data and Ethical Preparation", which will consequently support the GenAI system. As a result, *Participant 04* says "(...) this is almost an obvious relationship. When you are saying that the organizational strategic definition supports data management and data governance, which in turn will feed the GenAI system. You are already making this support link". When asked about the "is part of" connection that links the knowledge management processes enhanced by GenAI and the social and technical system, participants also found the link unnecessary as the connection is already implicit. For instance, *Participant 04* questions "if you look at the definition of knowledge management and knowledge, what is the origin of knowledge?", and the moderator answers "people", which leads us to how knowledge management processes are already related to the social system. *Participant 04* still adds "from the moment you have the social system and the technical system linked to the "GenAI system", they already have a connection to what the knowledge processes are, (...) so, in doubt, unless you have seen some direct connection between these things in the literature, which surely there is, but it is not explained here and it suggests doubts. (...) Therefore, I'd remove it." Here, it is specified the importance of leaving the diagram as simple as possible "anything that doesn't add value, it is best to simplify".

Regarding the "Data and Ethical Preparation" level, *participant 04* asks about the use of "oversight" and "execution", as if it is intended for researchers that some knowledge about data governance and data management is already there. (...) I interpret this as something that is meant to be interpreted initially by domain experts, (...) researchers who want to continue the research, (...) who have some connection to this area", continuing by saying that "(...) I don't know if it has value considering the interpretation of the model, (...) especially because you already have the explanation of data governance and data management in here".

Attending the "GenAI System", it was questioned how the presentation with the capabilities around it was understandable. Participants discussed how "Capabilities" is probably not the most indicated way to present it, encouraging to change to something like "Functions". *Participant 01* states that "there should be more, but you decided it was better not to include them. If they are the most relevant? I think so". At the same time, *Participant 00* wonders about these capabilities as a possible confusion between people and the machine, counseling that should be more like a collaboration aspect "(...) because, look, cognitive emulation, it is telling me that I have the ability to emulate a person, and also human-like interaction, (...) that can cause confusion because a native AI system is a piece of software at the end of the day. It is a piece of technology, not a person. So I think the capability here would be more of a collaboration aspect. (...) the aspect of it allowing collaboration between humans, I think it is much closer to social science that it emulating a person". Adding to the discussion, *Participant 04* states that what is intended, it seems, is "the concept she's using to categorize these things", reiterating that capabilities can be used but agrees with the other participant as it "leans more towards a term attributed to a person and, perhaps, what you mean instead of capabilities is functions". *Participant 02* also adds that there is no influential issue in using capabilities "because even in more technical articles, it is a word that is used quite often when we want to refer to the functions of the system". In the end, *Participant 01* and *Participant 04* offer a new idea for the design of the "GenAI System", changing the oval shape where the GenAI system is situated and change the arrows to a rectangle where the functions are represented along with GenAI system in the middle "if you invert that oval (...), you just have that rectangle, and instead of capabilities, you put it in the center, in bold, GenAI Systems, and the arrows, instead of actually going to an oval cycle, go to that rectangle. (...) because like that, none of them are specific, not do you have any arrow specifically linking to a capability", says *Participant 01*.

Considering design aspects associated with the structure and visual elements of the framework, *participant 04* argues that "(...) connections between the parts of the framework are too small, not emphasizing the connection or the reading mode of the framework, which in this case is from bottom to top. The arrows are small, the connection letters are small and there aren't many connections, so they should be more pronounced." Regarding the visual aspect, *participant 04* and *participant 02* emphasize that colors should be added since the framework is complex and has a lot of information "it might make sense to work on that a bit in a logical way by using colors, shapes, and captions".

In summary, participants emphasized the importance of simplifying the framework's visual structure and refining its terminology and relationships for better clarity and usability. Suggestions to remove redundant connections, clarify target audience assumptions, and reframe GenAI's capabilities as system functions reflect a shared desire to enhance interpretability without compromising conceptual depth. These insights offer valuable direction for improving the framework's accessibility and adaptability for both academic and practical contexts.

5.3.3 Data-Related Aspects and Ethical Considerations Feedback

The questions related to the "Data and Ethical Preparation", particularly the idea behind them was to encounter potential missing and misrepresented aspects in the data management and data governance boxes. Given participants' extensive organizational experience and research backgrounds, it was deemed crucial to inquire about the predominant data-related challenges and issues faced by organizations that they've been encountering. *Participant 04* promptly responds that the most common issue about data within organizations is "Data existence". It was also added by *Participant 01* the issue with data volume. At the same time, *Participant 02* mentions how organizations lack the existence of data, but "I think data integration, interoperability is also very important". Then, it was questioned if the six core data quality dimensions should be represented in the framework in any particular way. *Participant 1* remembers the importance of data consistency as for the data to hold quality needs to be consistent, however the participant states that "once again, I don't know if you should put what they were saying about interoperability there. Interoperability is not data quality. But at least the consistency part, I don't know if you should put it there explicitly too or say that consistency is part of data quality. Consistency is very important". In this line of thought, *Participant 04* addresses data existence but it also needs added accessibility because "many of the problems organizations face is that they have data but it is not accessible". *Participant 02* agrees with that statement saying that "yes, data access and, well, authorized data access was also what I remembered while looking at this part". Still in the question about the representation of data quality dimensions, *Participant 02* adds that "one thing that I remembered, but which is actually somewhat included in the compliance measures part, is for the data to be complete, not missing parts of the data".

Participant 01 presents an idea of creating a table with risks and challenges "where you identify the risks for the company and then the risk level, for example, to 0 to 5, and what is the impact level the company can have with that risk. (...) Not to complicate the framework (...), I would do this identification of risks separately". As a response to that interjection, *Participant 04* argues that risk management is already associated with the data and ethical preparation level and "it is not the objective of this framework, (...) otherwise it would cease to be a framework" if considering so many details about risk management and the data quality dimensions. Notwithstanding, it finished by saying that it "would be interesting to know, to transmit, (...) but I think this is another thing" that should be done separately instead of presenting it in the framework.

Concluding this part, ethical considerations were discussed as a paramount element that should be included everywhere, from the "Data and Ethical Preparation" to the Social and Technical System. When asked about where ethical aspects should be more prominent and active, the social or the technical system, participants rapidly and assertively responded that ethical considerations should be everywhere. *Participant 04*, "you need to address ethical considerations in all cycles", adding that "if GenAI is fed by information and data, if you guarantee ethical issues at the source, from the outset, at least a large part of the problems are solved (...)".

5.3.4 Integration of Sociotechnical Systems Theory Feedback

The Sociotechnical Systems Theory was considered in the questions according to the relevance of its existence within the framework. As the representation of this theory is mostly superficial and not the focus of the framework, it was decided that applying this theory is to start the discussion about the importance of a sociotechnical perspective, deconstructing the overly technocentric view of the GenAI research. As a result, participants were questioned about their opinion on the relevance and importance of incorporating this lens on this specific context while considering whether the social and technical system are properly represented. To start, *Participant 00* expresses how interoperability is one prevalent and relevant aspect in the technical system side, stating that "one aspect that I see very much in the technical system in the literature is system interoperability. (...) How to include it in the technical system? Yes, technical, mainly, integration. And that is a very big pain point in companies, system integration". Moreover, *Participant 02* interjects by reaffirming the importance of interoperability, "this technical interoperability can, therefore, be challenging as various companies have multiple systems, systems that are linked, and it is important to ensure communication among all of them". Considering the relevance of this sociotechnical system theory integration, *Participant 01* says that it is "(...) well-mentioned and differentiated. One very clear thing is the technical part. Another thing is the social part, and I think things are well divided here". It adds the importance of pondering the social system, as it is often neglected, "especially since it is the next step for Industry 5.0". As for organizations, the integration of a STS theory can be relevant to "demonstrate to the company the importance of the social aspect" but *Participant 00* offers a practical note affirming that "(...) practitioners, as they say in the academic language, they don't know what a social system and a technical system is. This is just a note, because maybe when it goes to the market, there will be an update in the language". When the join optimization, desired by the STS theory, is suggested in the discussion, *Participant 00* affirms how "some companies are more to the left, and some companies are more to the right. According to the literature, they are much more to the right than to the left, much more technical than social. (...) each company has its own (joint optimization)". However, once again, the objective of the framework is protested, as the sociotecnical system theory integration is not the focus of the framework and so, for the discussion, it is important to mention both sides as it is. *Participant 04* says that "I'm not saying which way it tends. (...) I think at this moment, what you are saying, at bottom, is that it is important to consider both components (...), that is the initial idea".

In conclusion, partipants affirmed the relevance of integrating sociotechnical systems theory as a means of emphasizing the interplay between social and technical dimensions within GenAI adoption. While acknowledging that the framework does not aim to deeply explore STS theory, its inclusion was seen as a valuable step toward encouraging more balanced, less technocentric perspectives. Feedback highlighted both the theoretical value and the practical challenges of conveying these concepts to non-academic audiences, reinforcing the need for clear terminology and contextual adaptation. Ultimately, the consensus supported mainting the dual representation as a foundational principle that signals the importance of joing consideration, even if not elaborated in full detail.

5.3.5 Final Feedback

At last, the question "Based on your organizational experience, do you think other aspects should be included in this framework? Is there any specific aspect that, after reading, after looking at the framework, you felt that is it missing?" was targeted at the group. The responses were related to the cultural and business aspect. *Participant 00* states that "this cultural aspect is decisive in the adoption and change of any technological thing. I have seen this over many years. The aspect of change management and cultural change would have to be included in some aspect, not in this framework, but I think it is something that needs to be thought through very carefully when bringing this framework into a company. That is, reaching into the minds and hearts of management, of the brains, of senior management, to show the value of this, because it starts there. They are the ones who sign the check to make it happen. And it is a very good process, years even, sometimes". With these considerations, the session concluded, having gathered insights, proposed future refinements, and made a final validation.

5.3.6 Results First Iteration

This section presents the Generative AI-Enhanced Knowledge Management Framework (GAKMF), incorporating refinements proposed during the focus group discussions. Each discipline is now represented by a distinct color — consistent with previous associations in the dissertation — to aid in differentiation and to help readers more easily identify relationships and positions within the framework. Connections have been made visually explicit, addressing their earlier lack of clarity and perceptibility. Within the technical system, “Interoperability Integration” has been added, having been identified as a critical and essential component in contemporary contexts. Regarding the "GenAI System", the previously central oval shape has been removed; its elements are now integrated into a larger rectangular structure labeled “Functions,” replacing the earlier term “Capabilities.” A further significant refinement involves the orientation of the framework: rather than progressing from bottom to top, it is now presented from top to bottom to enhance readability and logical flow. It is important to mention that this is a first iteration of the framework. In the future, additional focus groups and validations must be assured to refine even more, which will improve significantly the quality of the framework for the context that it was constructed for.

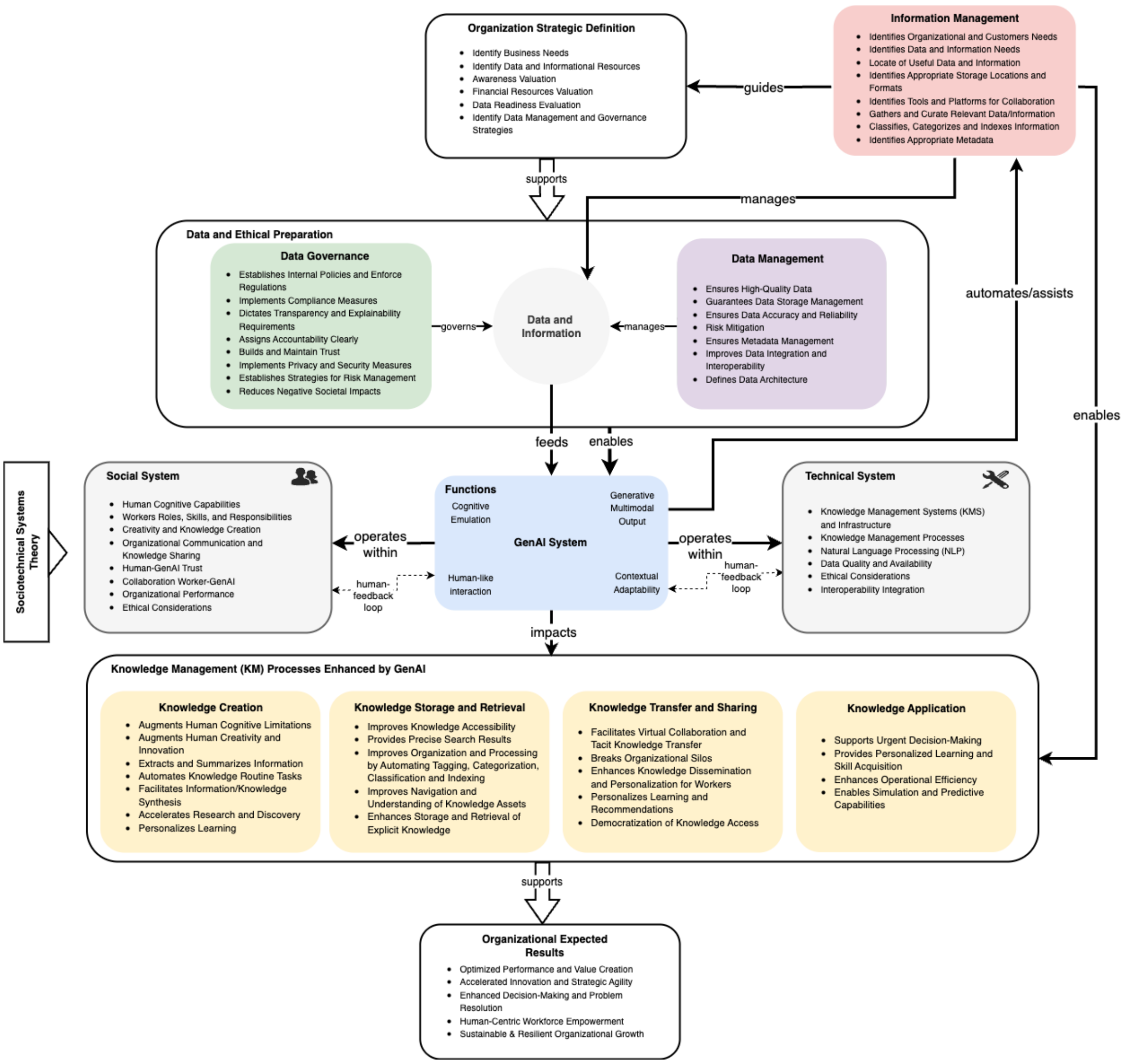

Figure 5.2: Generative AI-Enhanced Knowledge Management Framework (GAKMF) - First Iteration

Chapter 6

Conclusions and Future Work

As author (Davenport, 2018) notes, "One of the most important aspects of any strategy is how a key resource is going to affect your business." When an organization considers implementing a new technology for business advantage, a new strategy needs to be developed, as diverse and challenging factors are directly involved in this process. During the exploratory part of this dissertation, which involves gathering, reading, analyzing past and current literature, it was possible to conclude how organizations deal with vast amounts of data and information and how the interest for knowledge generation is an essential key for value creation. By understanding the necessity to leverage data, information, and knowledge assets, an organization rapidly grows an interest in current emergent technologies, capable of producing human-like outputs, that promise to shape worker's routines, operations, processes, and organizational performance.

The interest is universal, but opportunities are not equally distributed. All organizations are different, presenting specific needs, sizes, and resources, which clearly determines and limits access to technologies such as Generative AI. Even so, all organizations hold data, information, and people that are constantly producing and holding knowledge crucial to support business decisions. Understanding the vehicles that leverage these assets is paramount to effectively think about GenAI within organizational settings. Considering these facts, Knowledge Management is the primary focus of this dissertation. Analyzing its importance in the current technological paradigm is a necessity for organizations. It is evident how knowledge management enables competitive advantage and performance; how effectively manages knowledge resources residing within individual and collective forms.

Concurrently, GenAI appears as a sensational and rapid evolution of artificial intelligence, capable of efficiently creating knowledge, which is immediately positioned side by side with knowledge management. The connection between them is instinctive. If knowledge management is concerned in managing the creation, storage and retrieval, transfer and sharing, and application of knowledge, how can a technology that presents vast capabilities that challenge human cognitive ones, impact these same processes?

This dissertation aimed to respond to some of the impacts that this technology can have on KM processes, leading to positive and beneficial organizational results. Organizations are mostly worried to enhance their processes, but they forget about all the considerations and aspects that should be considered when adopting a technology that relies solely on data to properly function. As mentioned during this dissertation, organizations commonly struggle with the awareness of how their data assets currently are.

The questions that are relevant in this context are: What about data quality? What about data availability? This leads to an important realization. The adoption of GenAI, although technical, can't properly function without data management and governance strategies and measures. Organizations not only need to evaluate their data and information assets (increasing data readiness), but also must consider along business needs and goals, financial resources, and other factors that inform the organization how ready they are to adopt a technology such as Generative AI. The truth, as shown in some studies, is that a lot of companies don't know where and why they want to apply Generative AI into their business processes. The interest is bigger than the awareness. These impulsive decisions can easily compromise organization's resources and performance. To design and implement emergent technologies, a profound and detailed research in how GenAI can safely be designed and implemented into knowledge management processes, while attending social, human, organizational, and ethical aspects. Organizations can enhance KM processes with a well-structured organizational strategy, data and governance that protects and enables the functioning of the system. The framework developed for this dissertation aims to start the discussion on how these disciplines (IM, DM, DG, KM) are crucial for evolution of a technology that is capable of generating human-like outputs. Also, as the industrial paradigm is also evolving, it is paramount that principles are considered and appropriately aligned. As to not consider humans and their skills, roles, responsibilities is to contribute to a lack of trust in using the system, problems with aligning with stakeholder needs, exceed costs. Technologies need humans to govern and ensure that they are running according to what the organization, customers, employees require and necessitate. Thus, to achieve these needs, artifacts were created to support the beginning of the research in the field within a sociotechnical lens.

This dissertation set out to research the conceptual integration of Generative AI into knowledge management processes within organizational contexts, with particular attention to the interrelations among information management (IM), knowledge management (KM), data management (DM), and data governance (DG). Through a design Science Research (DSR) approach, the study developed and presented the Generative AI-Enhanced Knowledge Management Framework (GAKMF), a conceptual artifact that synthesizes the adoption of GenAI into knowledge management processes.

This research has demonstrated that GenAI technologies possess a transformative potential for organizational knowledge processes. This potential, nevertheless, depends on how well they mesh within social considerations, data management and governance practices, and organizational strategy. The GAKMF contributes theoretically by offering a multi-layered approach that incorporates GenAI into KM in a way that is not merely technological, but fundamentally sociotechnical, considering human aspects that are essential for the optimization of the technology. At the same time, since data is the most important asset for GenAI to work effectively, it is crucial that data management and data governance are considered when considering the adoption of GenAI to enhance knowledge management processes and, consequently, improve organizational performance.

An important outcome from the focus group evaluation (see Chapter 5) was the recognition of the target audience for this artifact. As several participants emphasized, the framework in its current form is most suitable for practitioners and researchers — those interested in advancing, validating, or customizing the artifact through additional conceptual or empirical work. Defining the target audience is essential to give the artifact a purpose and direction. Frameworks gain meaning when they are situated within a context of use. Without identifying for whom the framework is built, its scope becomes diffuse.

In this dissertation, the framework is primarily aimed at researchers and academically-oriented practitioners who wish to investigate the complex interrelations between GenAI, KM, and foundational data disciplines, specifically tending to a sociotechnical perspective. The current version functions as a conceptual and exploratory artifact, grounded in design science research. However, as was discussed during the focus group, in future iterations this framework could be reshaped and simplified for presentation to organizational stakeholders, including executives, decision-makers, and technology strategists, particularly once validated across specific industries or organizational use cases.

From a methodological perspective, this work exemplifies how conceptual modeling can serve as a valid form of artifact design within DSR, especially when empirical testing is constrained. While validation through a focus group is important, further empirical validation remains necessary to establish its robustness in specific organizational domains.

Ultimately, this dissertation responds to a pressing need: the absence of strategic guidance for integrating GenAI into KM processes. Rather than encouraging reactionary adoption, the research calls for a balanced approach grounded in sociotechnical alignment, ethical responsibility, data preparedness, and strategic planning. As technological paradigms continue to evolve, guiding principles must ensure that trust, collaboration, and human agency remain at the center of innovation.

6.1 Limitations

While this research provides a conceptual framework that involves relationships between disciplines with the intention to leverage the adoption of GenAI into KM processes, aiming to produce better organizational success, it is subject to certain limitations. First, the framework remains theoretical and has not been subjected to empirical validation or implemented within a use case, a real-world organizational context. Second, the feedback loop from practitioners and domain experts needs more iterations to extract more insights, contributing to better refinements of the framework. Finally, the research is mainly focused on the organizational context, and does not sufficiently account for other fields such as the manufacturing industry where information and knowledge flows are also intensive and in need of more research, especially in a sociotechnical lens. At the same time, besides the necessity for more framework iterations, it is necessary that validations of the discipline's conceptual models are performed to validate and improve them.

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6.2 Future Work

Building on the findings and limitations of this study, future research will explore the adoption of GenAI in the manufacturing industry through a sociotechnical perspective. This next phase will examine how GenAI intersects with human expertise, operational processes, and organizational structures in more nuanced and dynamic ways.

The aim is to expand the conceptual foundations of this dissertation into a doctoral research project. For that, it is intended to advance the results by focusing on the adoption of GenAI in the design of knowledge management processes within the manufacturing industry, focusing on a sociotechnical lens that considers human, social, and organizational aspects in the design and adoption of this technology. This proposed direction involves examining how GenAI impacts both workers and work processes beyond a technological approach (Hai et al., 2025; Bankins et al., 2024). It requires that research is done to capture how GenAI tools can be embedded in existing routines, how they interact with human decision-making, and how it can reshape the creation, dissemination and application of information and knowledge within a manufacturing industry, which are mostly knowledge-intensive environments.

By adhering to a sociotechnical perspective, paying equal attention to human roles, ethical, social, and technical aspects, it aligns with principles of Industry 5.0, which emphasize human-centric innovation, resilience, and sustainability when adopting and using technologies such as GenAI (Akbarighatar et al., 2023; Govers et al., 2019; Yu et al., 2022; Sai et al., 2025a). In this context, GenAI is not simply an automation tool but a co-actor in increasingly collaborative human-machine ecosystems. For that, future research must develop regulatory frameworks that address these aspects, ensuring that GenAI is developed while aligning with desired social and ethical aspects (Krakowski, 2025).

Although these are preliminary thoughts, it is expected to continue the work developed in this dissertation, considering current technological evolution across social elements. By this, this research is still superficial and necessitates more time to synthesize and produce knowledge for the scientific community, which is paramount in times where technology is evolving rapidly and presenting promising impacts for organizations and industries.

Ultimately, the aim is to refine the GAKMF framework to a point where it serves not only as an academic construct, but also as a practical tool for organizations seeking structured guidance on GenAI adoption, especially in the realm of KM. By doing so, this research contributes to a necessary and evolving conversation on how technologies capable of imitating human intelligence can be integrated responsibly, effectively, and meaningfully in knowledge-intensive domains.

6.3 Scientific Contribution

As part of the research workflow, a scientific article focused on the implication of GenAI for collaborative KM processes across individual, intra-, and inter-organizational context was developed and submitted during the dissertation process. The article, titled ***Generative AI as a Catalyst for Collaborative Knowledge Management: Impacts Across Individual, Intra, and Inter-Organizational levels***, was peer-reviewed, accepted, and presented at the ***26th IFIP/SOCOLNET Working Conference on Virtual Enterprises PRO-VE 2025)***.

References

ABRAHAM, Rene; SCHNEIDER, Johannes; VOM BROCKE, Jan, 2019. Data Governance: A Conceptual Framework, Structured Review, and Research Agenda. *International Journal of Information Management* [online]. Vol. 49, pp. 424–438 [visited on 2025-02-19]. ISSN 02684012. Available from DOI: 10.1016/j.ijinfomgt.2019.07.008.

AIIM, 2024. *New Study Reveals Crucial Role of Information Management in AI Success* [online]. [visited on 2025-06-20]. Available from: https://info.aiim.org/aiim-blog/new-study-reveals-crucial-role-of-information-management-in-ai-success.

AKBARIGHATAR, Pouria; PAPPAS, Ilias; VASSILAKOPOULOU, Polyxeni, 2023. A Sociotechnical Perspective for Responsible AI Maturity Models: Findings from a Mixed-Method Literature Review. *International Journal of Information Management Data Insights* [online]. Vol. 3, no. 2, p. 100193 [visited on 2025-06-15]. ISSN 2667-0968. Available from DOI: 10.1016/j.jjimei.2023.100193.

AKHTAR, Pervaiz; GHOURI, Arsalan Mujahid; ASHRAF, Aniqa; LIM, Jia Jia; KHAN, Naveed R; MA, Shuang, 2024. Smart Product Platforming Powered by AI and Generative AI: Personalization for the Circular Economy. *International Journal of Production Economics* [online]. Vol. 273, p. 109283 [visited on 2024-11-03]. ISSN 0925-5273. Available from DOI: 10.1016/j.ijpe.2024.109283.

ALAVI, Maryam; LEIDNER, Dorothy; MOUSAVI, Reza, 2024. A Knowledge Management Perspective of Generative Artificial Intelligence. *Journal of the Association for Information Systems*. Vol. 25, no. 1, pp. 1–12. ISSN 1536-9323. Available from DOI: 10.17705/1jais.00859.

ALAVI, Maryam; LEIDNER, Dorothy E., 2001. Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly* [online]. Vol. 25, no. 1, pp. 107–136 [visited on 2024-08-13]. ISSN 0276-7783. Available from DOI: 10.2307/3250961.

AMANKWAH-AMOAH, Joseph; ABDALLA, Samar; MOGAJI, Emmanuel; ELBANNA, Amany; DWIVEDI, Yogesh K., 2024. The Impending Disruption of Creative Industries by Generative AI: Opportunities, Challenges, and Research Agenda. *International Journal of Information Management* [online]. Vol. 79, p. 102759 [visited on 2024-11-29]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2024.102759.

ANDRES, B.; URZE, P.; ARAUJO, E.; CAMARINHA-MATOS, L. M., 2025. ARTIFICIAL INTELLIGENCE USE IN COLLABORATIVE NETWORK PROCESSES. *Journal of Industrial Information Integration* [online], p. 100883 [visited on 2025-06-02]. ISSN 2452-414X. Available from DOI: 10.1016/j.jii.2025.100883.

ANDRES, Beatriz; FERNANDEZ-GARCIA, David; URZE, Pala; ARAUJO, Emilia, 2024. *Artificial Intelligence Use in Collaborative Network Processes* [online]. 2024-03-19. [visited on 2025-06-17]. Available from DOI: 10.21203/rs.3.rs-4106721/v1.

AROMAA, Susanna; HEIKKILÄ, Päivi; JURVANSUU, Marko; PEHLIVAN, Selen; VÄÄRÄ, Teijo; JURMU, Marko, 2025. Company Perspectives of Generative Artificial Intelligence in Industrial Work. *Procedia Computer Science* [online]. Vol. 253, pp. 217–226 [visited on 2025-05-15]. ISSN 18770509. Available from DOI: 10.1016/j.procs.2025.01.085.

ATTARD, Judie; BRENNAN, Rob, 2018. Challenges in Value-Driven Data Governance. In: PANETTO, Hervé; DEBRUYNE, Christophe; PROPER, Henderik A.; ARDAGNA, Claudio Agostino; ROMAN, Dumitru; MEERSMAN, Robert (eds.). *On the Move to Meaningful Internet Systems. OTM 2018 Conferences* [online]. Cham: Springer International Publishing. Vol. 11230, pp. 546–554 [visited on 2025-02-20]. Available from DOI: 10.1007/978-3-030-02671-4_33.

AUNIMO, Lili; KAUTTONEN, Janne; LAHTINEN, Anna; LAGSTEDT, Altti; ALAMÄKI, Ari, 2023. Factors Affecting the Adoption of AI by Organizations - From the Perspective of Knowledge Workers. In: CAMARINHA-MATOS, Luis M.; BOUCHER, Xavier; ORTIZ, Angel (eds.). *Collaborative Networks in Digitalization and Society 5.0*. Cham: Springer Nature Switzerland, pp. 467–481. Available from DOI: 10.1007/978-3-031-42622-3_33.

BAIER, Paul; SVIOKLA, John J., 2025. Turbocharging Organizational Learning With GenAI. *MIT Sloan Management Review* [online] [visited on 2025-03-14]. Available from: https://sloanreview.mit.edu/article/turbocharging-organizational-learning-with-genai/.

BANH, Leonardo; STROBEL, Gero, 2023. Generative Artificial Intelligence. *Electronic Markets* [online]. Vol. 33, no. 1, p. 63 [visited on 2024-12-22]. ISSN 1422-8890. Available from DOI: 10.1007/s12525-023-00680-1.

BANKINS, Sarah; OCAMPO, Anna Carmella; MARRONE, Mauricio; RESTUBOG, Simon Lloyd D.; WOO, Sang Eun, 2024. A Multilevel Review of Artificial Intelligence in Organizations: Implications for Organizational Behavior Research and Practice. *Journal of Organizational Behavior* [online]. Vol. 45, no. 2, pp. 159–182 [visited on 2025-05-20]. ISSN 1099-1379. Available from DOI: 10.1002/job.2735.

BARRENECHEA, Oscar; MENDIETA, Aaron; ARMAS, Jimmy; MADRID, Juan Manuel, 2019. Data Governance Reference Model to Streamline the Supply Chain Process in SMEs. In: *2019 IEEE XXVI International Conference on Electronics, Electrical Engineering and Computing (INTERCON)* [online]. Lima, Peru: IEEE, pp. 1–4 [visited on 2025-02-20]. Available from DOI: 10.1109/INTERCON.2019.8853634.

BAXTER, Gordon; SOMMERVILLE, Ian, 2011. Socio-Technical Systems: From Design Methods to Systems Engineering. *Interacting with Computers* [online]. Vol. 23, no. 1, pp. 4–17 [visited on 2025-06-13]. ISSN 0953-5438. Available from DOI: 10.1016/j.intcom.2010.07.003.

BEESLEY, Lisa G.A.; COOPER, Chris, 2008. Defining Knowledge Management (KM) Activities: Towards Consensus. *Journal of Knowledge Management* [online]. Vol. 12, no. 3, pp. 48–62 [visited on 2025-01-24]. ISSN 1367-3270. Available from DOI: 10.1108/13673270810875859.

BENBYA, Hind; DAVENPORT, Thomas H.; PACHIDI, Stella, 2020. *Artificial Intelligence in Organizations: Current State and Future Opportunities* [online]. Rochester, NY, 2020-12-03 [visited on 2024-12-12]. No. 3741983. Available from DOI: 10.2139/ssrn.3741983.

BENBYA, Hind; DEAKIN UNIVERSITY; STRICH, Franz; DEAKIN UNIVERSITY; TAMM, Toomas; DEAKIN UNIVERSITY, 2024. Navigating Generative Artificial Intelligence Promises and Perils for Knowledge and Creative Work. *Journal of the Association for Information Systems* [online]. Vol. 25, no. 1, pp. 23–36 [visited on 2024-08-13]. ISSN 15369323. Available from DOI: 10.17705/1jais.00861.

BLAIR, David C., 2002. Knowledge Management: Hype, Hope, or Help? [online] [visited on 2024-12-20]. ISSN 1532-2882. Available from DOI: 10.1002/asi.10113.

BÖHM, Karsten; DURST, Susanne, 2025. Knowledge Management in the Age of Generative Artificial Intelligence – from SECI to GRAI. *VINE Journal of Information and Knowledge Management Systems* [online]. Vol. ahead-of-print [visited on 2025-06-18]. ISSN 2059-5905. Available from DOI: 10.1108/VJIKMS-10-2024-0357.

BRYNJOLFSSON, Erik; LI, Danielle; RAYMOND, Lindsey R., 2023. *Generative AI at Work* [online]. 2023-04. [visited on 2024-11-15]. Working Paper Series, no. 31161. Available from DOI: 10.3386/w31161.

CHOO, C. W., 1996. The Knowing Organization: How Organizations Use Information to Construct Meaning, Create Knowledge and Make Decisions. *International Journal of Information Management* [online]. Vol. 16, no. 5, pp. 329–340 [visited on 2025-06-11]. ISSN 0268-4012. Available from DOI: 10.1016/0268-4012(96)00020-5.

CHOO, Chun Wei, 2002. *Information Management for the Intelligent Organization: The Art of Scanning the Environment*. Information Today, Inc. Available from Google Books: ID1Dwy9UfmsC.

CHOWDHURY, Soumyadeb; BUDHWAR, Pawan; DEY, Prasanta Kumar; JOEL-EDGAR, Sian; ABADIE, Amelie, 2022. AI-employee Collaboration and Business Performance: Integrating Knowledge-Based View, Socio-Technical Systems and Organisational Socialisation Framework. *Journal of Business Research* [online]. Vol. 144, pp. 31–49 [visited on 2024-12-15]. ISSN 0148-2963. Available from DOI: 10.1016/j.jbusres.2022.01.069.

DALKIR, Kimiz, 2023. *Knowledge Management in Theory and Practice*. Fourth edition. Cambridge, Massachusetts: The MIT Press.

DAVENPORT, Thomas H., 2018. *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*. MIT Press. ISBN 978-0-262-03917-8. Available from Google Books: JzNwDwAAQBAJ.

DAVENPORT, Thomas H.; PRUSAK, Laurence, 1998. *Working Knowledge: How Organizations Manage What They Know*. Harvard Business Press.

DE SIMONE, Valentina; PASQUALE, Valentina Di; MIRANDA, Salvatore, 2023. An Overview on the Use of AI/ML in Manufacturing MSMEs: Solved Issues, Limits, and Challenges. *Procedia Computer Science* [online]. Vol. 217, pp. 1820–1829 [visited on 2025-02-21]. ISSN 18770509. Available from DOI: 10.1016/j.procs.2022.12.382.

DETLOR, Brian, 2010. Information Management. *International Journal of Information Management* [online]. Vol. 30, no. 2, pp. 103–108 [visited on 2025-01-28]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2009.12.001.

DOANH, Doung Cong; DUFEK, Zdenek; EJDYS, Joanna; GINEVIČIUS, Romualdas; KORZYNSKI, Pawel; MAZUREK, Grzegorz; PALISZKIEWICZ, Joanna; WACH, Krzysztof; ZIEMBA, Ewa, 2023. Generative AI in the Manufacturing Process: Theoretical Considerations. *Engineering Management in Production and Services* [online]. Vol. 15, no. 4, pp. 76–89 [visited on 2025-04-29]. ISSN 2543-912X. Available from DOI: 10.2478/emj-2023-0029.

DUAN, Yanqing; EDWARDS, John S.; DWIVEDI, Yogesh K., 2019. Artificial Intelligence for Decision Making in the Era of Big Data - Evolution, Challenges and Research Agenda. *INTERNATIONAL JOURNAL OF INFORMATION MANAGEMENT* [online]. Vol. 48, pp. 63–71 [visited on 2024-11-26]. ISSN 0268-4012, ISSN 1873-4707. Available from DOI: 10.1016/j.ijinfomgt.2019.01.021.

DWIVEDI, Yogesh K.; HUGHES, Laurie; ISMAGILOVA, Elvira; AARTS, Gert; COOMBS, Crispin; CRICK, Tom; DUAN, Yanqing; DWIVEDI, Rohita; EDWARDS, John; EIRUG, Aled; GALANOS, Vassilis; ILAVARASAN, P. Vigneswara; JANSSEN, Marijn; JONES, Paul; KAR, Arpan Kumar; KIZGIN, Hatice; KRONEMANN, Bianca; LAL, Banita; LUCINI, Biagio; MEDAGLIA, Rony; LE MEUNIER-FITZHUGH, Kenneth; LE MEUNIER-FITZHUGH, Leslie Caroline; MISRA, Santosh; MOGAJI, Emmanuel; SHARMA, Sujeet Kumar; SINGH, Jang Bahadur; RAGHAVAN, Vishnupriya; RAMAN, Ramakrishnan; RANA, Nripendra P.; SAMOTHRAKIS, Spyridon; SPENCER, Jak; TAMILMANI, Kuttimani; TUBADJI, Annie; WALTON, Paul; WILLIAMS, Michael D., 2021. Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy. *International Journal of Information Management* [online]. Vol. 57, p. 101994 [visited on 2025-06-02]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2019.08.002.

DWIVEDI, Yogesh K.; KSHETRI, Nir; HUGHES, Laurie; SLADE, Emma Louise; JEYARAJ, Anand; KAR, Arpan Kumar; BAABDULLAH, Abdullah M.; KOOHANG, Alex; RAGHAVAN, Vishnupriya; AHUJA, Manju; ALBANNA, Hanaa; ALBASHRAWI, Mousa Ahmad; AL-BUSAIDI, Adil S.; BALAKRISHNAN, Janarthanan; BARLETTE, Yves; BASU, Sriparna; BOSE, Indranil; BROOKS, Laurence; BUHALIS, Dimitrios; CARTER, Lemuria; CHOWDHURY, Soumyadeb; CRICK, Tom; CUNNINGHAM, Scott W.; DAVIES, Gareth H.; DAVISON, Robert M.; DÉ, Rahul; DENNEHY, Denis; DUAN, Yanqing; DUBEY, Rameshwar; DWIVEDI, Rohita; EDWARDS, John S.; FLAVIÁN, Carlos; GAULD, Robin; GROVER, Varun; HU, Mei-Chih; JANSSEN, Marijn; JONES, Paul; JUNGLAS, Iris; KHORANA, Sangeeta; KRAUS, Sascha; LARSEN, Kai R.; LATREILLE, Paul; LAUMER, Sven; MALIK, F. Tegwen; MARDANI, Abbas; MARIANI, Marcello; MITHAS, Sunil; MOGAJI, Emmanuel; NORD, Jeretta Horn; O'CONNOR, Siobhan; OKUMUS, Fevzi; PAGANI, Margherita; PANDEY, Neeraj; PAPAGIANNIDIS, Savvas; PAPPAS, Ilias O.; PATHAK, Nishith; PRIES-HEJE, Jan; RAMAN, Ramakrishnan; RANA, Nripendra P.; REHM, Sven-Volker; RIBEIRO-NAVARRETE, Samuel; RICHTER, Alexander; ROWE, Frantz; SARKER, Suprateek; STAHL, Bernd Carsten; TIWARI, Manoj Kumar; van der AALST, Wil; VENKATESH, Viswanath; VIGLIA, Giampaolo; WADE, Michael; WALTON, Paul; WIRTZ, Jochen; WRIGHT, Ryan, 2023. Opinion Paper: "So What If ChatGPT Wrote It?" Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy. *International Journal of Information Management* [online]. Vol. 71, p. 102642 [visited on 2025-01-26]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2023.102642.

EARLEY, Seth, 2023. What Executives Need to Know about Knowledge Management, Large Language Models and Generative AI. *Applied Marketing Analytics: The Peer-Reviewed Journal* [online]. Vol. 9, no. 3, p. 215 [visited on 2024-11-15]. ISSN 2054-7552. Available from DOI: 10.69554/YQBV7690.

EARLEY, Susan; HENDERSON, Deborah; ASSOCIATION, Data Management (eds.), 2017. *DAMA-DMBOK: Data Management Body of Knowledge*. 2nd edition. Basking Ridge, New Jersey: Technics Publications.

EDGAR, William B; ALBRIGHT, Kendra S, 2023. Knowledge Management Activities: Conceptual Foundations and Research Issues. *Journal of Information Science* [online]. Vol. 49, no. 6, pp. 1656–1676 [visited on 2024-08-13]. ISSN 0165-5515, ISSN 1741-6485. Available from DOI: 10.1177/01655515211069538.

ELOUNDOU, Tyna; MANNING, Sam; MISHKIN, Pamela; ROCK, Daniel, 2023. *GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models* [online]. 2023-08-21. [visited on 2025-01-26]. Available from DOI: 10.48550/arXiv.2303.10130.

ENGELS, Barbara, 2019. Data Governance as the Enabler of the Data Economy. *Intereconomics* [online]. Vol. 54, no. 4, pp. 216–222 [visited on 2025-02-20]. ISSN 0020-5346, ISSN 1613-964X. Available from DOI: 10.1007/s10272-019-0827-y.

ESCOBAR, Carlos A.; CANTORAL-CEBALLOS´, Jose Antonio; TWOREK, Michael; YANG, Kai; MORALES-MENENDEZ, Ruben, 2025. *Generative Ai for Manufacturing Innovation: A Comprehensive Review with Case Studies* [online]. [visited on 2025-05-16]. Available from DOI: 10.2139/ssrn.5188841.

FAHEY, Liam; PRUSAK, Laurence, 1998. The Eleven Deadliest Sins of Knowledge Management. *California Management Review* [online]. Vol. 40, no. 3, pp. 265–276 [visited on 2025-01-15]. ISSN 0008-1256, ISSN 2162-8564. Available from DOI: 10.2307/41165954.

FEUERRIEGEL, Stefan; HARTMANN, Jochen; JANIESCH, Christian; ZSCHECH, Patrick, 2024. Generative AI. *Business & Information Systems Engineering* [online]. Vol. 66, no. 1, pp. 111–126 [visited on 2025-01-28]. ISSN 1867-0202. Available from DOI: 10.1007/s12599-023-00834-7.

FORMANEK, Matus, 2024. Exploring the Potential of Large Language Models and Generative Artificial Intelligence (GPT): Applications in Library and Information Science. *Journal of Librarianship and Information Science* [online], p. 09610006241241066 [visited on 2024-11-24]. ISSN 0961-0006. Available from DOI: 10.1177/09610006241241066.

GHOBAKHLOO, M.; FATHI, M.; IRANMANESH, M.; VILKAS, M.; GRYBAUSKAS, A.; AMRAN, A., 2024. Generative Artificial Intelligence in Manufacturing: Opportunities for Actualizing Industry 5.0 Sustainability Goals. *Journal of Manufacturing Technology Management*. Vol. 35, no. 9, pp. 94–121. Available from DOI: 10.1108/JMTM-12-2023-0530.

GHOBAKHLOO, Morteza; IRANMANESH, Mohammad; MORALES, Manuel E.; NILASHI, Mehrbakhsh; AMRAN, Azlan, 2023. Actions and Approaches for Enabling Industry 5.0-Driven Sustainable Industrial Transformation: A Strategy Roadmap. *Corporate Social Responsibility and Environmental Management* [online]. Vol. 30, no. 3, pp. 1473–1494 [visited on 2025-05-26]. ISSN 1535-3966. Available from DOI: 10.1002/csr.2431.

GOVERS, Mark; AMELSVOORT, Pierre van, 2019. A Socio-Technical Perspective on the Digital Era: The Lowlands View. *European Journal of Workplace Innovation* [online]. Vol. 4, no. 2 [visited on 2025-06-15]. ISSN 2387-4570. Available from DOI: 10.46364/ejwi.v4i2.589.

GRANT, Robert M., 1996. Toward a Knowledge-Based Theory of the Firm. *Strategic Management Journal* [online]. Vol. 17, no. S2, pp. 109–122 [visited on 2024-10-11]. ISSN 1097-0266. Available from DOI: 10.1002/smj.4250171110.

GROVER, Varun; DAVENPORT, Thomas H., 2001. General Perspectives on Knowledge Management: Fostering a Research Agenda. *Journal of Management Information Systems* [online]. Vol. 18, no. 1, pp. 5–21 [visited on 2025-01-14]. ISSN 0742-1222, ISSN 1557-928X. Available from DOI: 10.1080/07421222.2001.11045672.

GRYBAUSKAS, Andrius, 2024. Industry 5.0 and Artificial Semi-General Intelligence. Exploring Future Challenges and Opportunities Within Industries and Societies. In: NOUSALA, Susu; METCALF, Gary; ING, David (eds.). *Industry 4.0 to Industry 5.0: Explorations in the Transition from a Techno-economic to a Socio-technical Future* [online]. Singapore: Springer Nature, pp. 93–112 [visited on 2024-10-16]. Available from DOI: 10.1007/978-981-99-9730-5_5.

GUARINO, Nicola; GUIZZARDI, Giancarlo; MYLOPOULOS, John, 2020. On the Philosophical Foundations of Conceptual Models. In: *Information Modelling and Knowledge Bases XXXI* [online]. IOS Press, pp. 1–15 [visited on 2025-06-29]. Available from DOI: 10.3233/FAIA200002.

HAI, Shenyang; LONG, Tianyi; HONORA, Andreawan; JAPUTRA, Arnold; GUO, Tengfei, 2025. The Dark Side of Employee-Generative AI Collaboration in the Workplace: An Investigation on Work Alienation and Employee Expediency. *International Journal of Information Management* [online]. Vol. 83, p. 102905 [visited on 2025-05-20]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2025.102905.

HARIDASAN, Praveen Kotholliparambil; JAWALE, Hemant, 2024. Generative AI in Manufacturing: A Review of Innovations, Challenges, and Future Prospects. *Journal of Artificial Intelligence, Machine Learning and Data Science* [online]. Vol. 2, no. 2, pp. 1418–1424 [visited on 2025-04-29]. ISSN 25839888. Available from DOI: 10.51219/JAIMLD/praveen-haridasan/321.

HERRMANN, Thomas; PFEIFFER, Sabine, 2023. Keeping the Organization in the Loop: A Socio-Technical Extension of Human-Centered Artificial Intelligence. *AI & SOCIETY* [online]. Vol. 38, no. 4, pp. 1523–1542 [visited on 2025-05-27]. ISSN 1435-5655. Available from DOI: 10.1007/s00146-022-01391-5.

HEVNER, Alan R, 2007. A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*. Vol. 19, no. 2, pp. 87–92. ISSN 0905-0167.

HEVNER, Alan R; MARCH, Salvatore T; PARK, Jinsoo; RAM, Sudha, 2004. Design Science in Information Systems Research.

HEVNER, Chatterjee, 2010. Design Science Research in Information Systems Good. In: *Design Research in Information Systems*. Springer Science+Business Media, pp. 9–22. Available from DOI: 10.1007/978-1-4419-5653-8_2.

HOLMSTRÖM, Jonny; CARROLL, Noel, 2024. How Organizations Can Innovate with Generative AI. *Business Horizons* [online] [visited on 2024-12-10]. ISSN 0007-6813. Available from DOI: 10.1016/j.bushor.2024.02.010.

JANSSEN, Marijn, 2025. Responsible Governance of Generative AI: Conceptualizing GenAI as Complex Adaptive Systems. *Policy and Society* [online], puae040 [visited on 2025-03-21]. ISSN 1449-4035, ISSN 1839-3373. Available from DOI: 10.1093/polsoc/puae040.

JARRAHI, Mohammad Hossein; ASKAY, David; ESHRAGHI, Ali; SMITH, Preston, 2023. Artificial Intelligence and Knowledge Management: A Partnership between Human and AI. *Business Horizons* [online]. Vol. 66, no. 1, pp. 87–99 [visited on 2024-12-15]. ISSN 0007-6813. Available from DOI: 10.1016/j.bushor.2022.03.002.

JIN, Jian; YANG, Mingyue; HU, Huicong; GUO, Xin; LUO, Jianxi; LIU, Ying, 2024. Empowering Design Innovation Using AI-generated Content. *Journal of Engineering Design* [online]. Vol. 0, no. 0, pp. 1–18 [visited on 2024-12-10]. ISSN 0954-4828. Available from DOI: 10.1080/09544828.2024.2401751.

KACZOROWSKA-SPYCHALSKA, D.; KOTULA, N.; MAZUREK, G.; SUŁKOWSKI, Ł., 2024. GENERATIVE AI AS SOURCE OF CHANGE OF KNOWLEDGE MANAGEMENT PARADIGM. *Human Technology*. Vol. 20, no. 1, pp. 131–154. Available from DOI: 10.14254/1795-6889.2024.20-1.7.

KANBACH, Dominik K.; HEIDUK, Louisa; BLUEHER, Georg; SCHREITER, Maximilian; LAHMANN, Alexander, 2024. The GenAI Is out of the Bottle: Generative Artificial Intelligence from a Business Model Innovation Perspective. *Review of Managerial Science* [online]. Vol. 18, no. 4, pp. 1189–1220 [visited on 2025-03-22]. ISSN 1863-6683, ISSN 1863-6691. Available from DOI: 10.1007/s11846-023-00696-z.

KARKOŠKOVÁ, Soňa, 2023. Data Governance Model To Enhance Data Quality In Financial Institutions. *Information Systems Management* [online]. Vol. 40, no. 1, pp. 90–110 [visited on 2025-02-19]. ISSN 1058-0530, ISSN 1934-8703. Available from DOI: 10.1080/10580530.2022.2042628.

KEBEDE, Gashaw, 2010. Knowledge Management: An Information Science Perspective. *International Journal of Information Management* [online]. Vol. 30, no. 5, pp. 416–424 [visited on 2024-11-30]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2010.02.004.

KELLOGG, Katherine C.; LIFSHITZ, Hila; RANDAZZO, Steven; MOLLICK, Ethan; DELL'ACQUA, Fabrizio; MCFOWLAND, Edward; CANDELON, François; LAKHANI, Karim R., 2025. Novice Risk Work: How Juniors Coaching Seniors on Emerging Technologies Such as Generative AI Can Lead to Learning Failures. *Information and Organization* [online]. Vol. 35, no. 1, p. 100559 [visited on 2025-03-13]. ISSN 14717727. Available from DOI: 10.1016/j.infoandorg.2025.100559.

KHAN, Salman; MEHMOOD, Shafaqat; KHAN, Safeer Ullah, 2024. Navigating Innovation in the Age of AI: How Generative AI and Innovation Influence Organizational Performance in the Manufacturing Sector. *Journal of Manufacturing Technology Management* [online]. Vol. ahead-of-print [visited on 2024-12-16]. ISSN 1758-7786. Available from DOI: 10.1108/JMTM-06-2024-0302.

KIANGALA, Kahiomba Sonia; WANG, Zenghui, 2024. An Experimental Hybrid Customized AI and Generative AI Chatbot Human Machine Interface to Improve a Factory Troubleshooting Downtime in the Context of Industry 5.0. *The International Journal of Advanced Manufacturing Technology* [online]. Vol. 132, no. 5, pp. 2715–2733 [visited on 2025-06-19]. ISSN 1433-3015. Available from DOI: 10.1007/s00170-024-13492-0.

KORZYNSKI, Pawel; MAZUREK, Grzegorz; ALTMANN, Andreas; EJDYS, Joanna; KAZLAUSKAITE, Ruta; PALISZKIEWICZ, Joanna; WACH, Krzysztof; ZIEMBA, Ewa, 2023. Generative Artificial Intelligence as a New Context for Management Theories: Analysis of ChatGPT. *Central European Management Journal* [online]. Vol. 31, no. 1, pp. 3–13 [visited on 2024-11-19]. ISSN 2658-2430. Available from DOI: 10.1108/CEMJ-02-2023-0091.

KRAKOWSKI, Sebastian, 2025. Human-AI Agency in the Age of Generative AI. *Information and Organization* [online]. Vol. 35, no. 1, p. 100560 [visited on 2025-03-11]. ISSN 14717727. Available from DOI: 10.1016/j.infoandorg.2025.100560.

KRUGER, C. J.; JOHNSON, Roy D., 2010. Information Management as an Enabler of Knowledge Management Maturity: A South African Perspective. *International Journal of Information Management* [online]. Vol. 30, no. 1, pp. 57–67 [visited on 2024-12-20]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2009.06.007.

KUMAR, Aman; SHANKAR, Amit; HOLLEBEEK, Linda D.; BEHL, Abhishek; LIM, Weng Marc, 2025. Generative Artificial Intelligence (GenAI) Revolution: A Deep Dive into GenAI Adoption. *Journal of Business Research* [online]. Vol. 189, p. 115160 [visited on 2025-03-11]. ISSN 01482963. Available from DOI: 10.1016/j.jbusres.2024.115160.

KUSIAK, Andrew, 2025. Generative Artificial Intelligence in Smart Manufacturing. *Journal of Intelligent Manufacturing* [online]. Vol. 36, no. 1, pp. 1–3 [visited on 2025-04-30]. ISSN 1572-8145. Available from DOI: 10.1007/s10845-024-02480-6.

LAI, Hsiangchu; CHU, Tsai-Hsin, 2000. Knowledge Management: A Review of Theoretical Frameworks and Industrial Cases. In: *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences* [online] [visited on 2025-06-11]. Available from DOI: 10.1109/HICSS.2000.926705.

LATINO, Maria Elena, 2025. A Maturity Model for Assessing the Implementation of Industry 5.0 in Manufacturing SMEs: Learning from Theory and Practice. *Technological Forecasting and Social Change* [online]. Vol. 214, p. 124045 [visited on 2025-05-22]. ISSN 0040-1625. Available from DOI: 10.1016/j.techfore.2025.124045.

LEE, Hao-Ping (Hank); SARKAR, Advait; TANKELEVITCH, Lev; DROSOS, Ian; RINTEL, Sean; BANKS, Richard; WILSON, Nicholas, 2025. The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers. In: *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* [online]. Yokohama Japan: ACM, pp. 1–22 [visited on 2025-06-28]. ISBN 979-8-4007-1394-1. Available from DOI: 10.1145/3706598.3713778.

LEE, Jin Sub; KIM, Jisun; KIM, Philip M., 2023. Score-Based Generative Modeling for de Novo Protein Design. *Nature Computational Science*. Vol. 3, no. 5, pp. 382–392. ISSN 2662-8457. Available from DOI: 10.1038/s43588-023-00440-3.

LENG, Jiewu; SHA, Weinan; WANG, Baicun; ZHENG, Pai; ZHUANG, Cunbo; LIU, Qiang; WUEST, Thorsten; MOURTZIS, Dimitris; WANG, Lihui, 2022. Industry 5.0: Prospect and Retrospect. *Journal of Manufacturing Systems* [online]. Vol. 65, pp. 279–295 [visited on 2025-05-23]. ISSN 0278-6125. Available from DOI: 10.1016/j.jmsy.2022.09.017.

LEONI, Luna; GUELI, Ginetta; ARDOLINO, Marco; PANIZZON, Mateus; GUPTA, Shivam, 2024. AI-empowered KM Processes for Decision-Making: Empirical Evidence from Worldwide Organisations. *Journal of Knowledge Management* [online]. Vol. 28, no. 11, pp. 320–347 [visited on 2024-12-20]. ISSN 1758-7484. Available from DOI: 10.1108/JKM-03-2024-0262.

LI, Lixu; LIU, Yaoqi; JIN, Yong; CHENG, T.C. Edwin; ZHANG, Qianjun, 2024. Generative AI-enabled Supply Chain Management: The Critical Role of Coordination and Dynamism. *International Journal of Production Economics* [online]. Vol. 277, p. 109388 [visited on 2025-05-15]. ISSN 09255273. Available from DOI: 10.1016/j.ijpe.2024.109388.

LIANG, Percy; BOMMASANI, Rishi; LEE, Tony; TSIPRAS, Dimitris; SOYLU, Dilara; YASUNAGA, Michihiro; ZHANG, Yian; NARAYANAN, Deepak; WU, Yuhuai; KUMAR, Ananya; NEWMAN, Benjamin; YUAN, Binhang; YAN, Bobby; ZHANG, Ce; COSGROVE, Christian; MANNING, Christopher D.; RÉ, Christopher; ACOSTA-NAVAS, Diana; HUDSON, Drew A.; ZELIKMAN, Eric; DURMUS, Esin; LADHAK, Faisal; RONG, Frieda; REN, Hongyu; YAO, Huaxiu; WANG, Jue; SANTHANAM, Keshav; ORR, Laurel; ZHENG, Lucia; YUKSEKGONUL, Mert; SUZGUN, Mirac; KIM, Nathan; GUHA, Neel; CHATTERJI, Niladri; KHATTAB, Omar; HENDERSON, Peter; HUANG, Qian; CHI, Ryan; XIE, Sang Michael; SANTURKAR, Shibani; GANGULI, Surya; HASHIMOTO, Tatsunori; ICARD, Thomas; ZHANG, Tianyi; CHAUDHARY, Vishrav; WANG, William; LI, Xuechen; MAI, Yifan; ZHANG, Yuhui; KOREEDA, Yuta, 2023. *Holistic Evaluation of Language Models* [online]. 2023-10-01. [visited on 2024-11-26]. Available from arXiv: 2211.09110.

LIEBOWITZ, J, 2001. Knowledge Management and Its Link to Artificial Intelligence. *Expert Systems with Applications* [online]. Vol. 20, no. 1, pp. 1–6 [visited on 2024-12-20]. ISSN 0957-4174. Available from DOI: 10.1016/S0957-4174(00)00044-0.

LIU, Chang, 2024. The Application of AI and Product Innovation Efficiency: The Role of Knowledge Innovation under SECI Model. *Aslib Journal of Information Management* [online]. Vol. ahead-of-print [visited on 2024-12-20]. ISSN 2050-3814. Available from DOI: 10.1108/AJIM-04-2024-0348.

LIU, Gang; KIANTO, Aino; TSUI, Eric, 2022. Knowledge Management Technologies and Organizational Performance: A Meta-Analytic Study. *Industrial Management & Data Systems* [online]. Vol. 123, no. 2, pp. 386–408 [visited on 2024-12-21]. ISSN 0263-5577. Available from DOI: 10.1108/IMDS-02-2022-0121.

MA, Liang; YU, Peng; ZHANG, Xin; WANG, Gaoshan; HAO, Feifei, 2024. How AI Use in Organizations Contributes to Employee Competitive Advantage: The Moderating Role of Perceived Organization Support. *Technological Forecasting and Social Change* [online]. Vol. 209, p. 123801 [visited on 2024-12-15]. ISSN 0040-1625. Available from DOI: 10.1016/j.techfore.2024.123801.

MAKARIUS, Erin E.; MUKHERJEE, Debmalya; FOX, Joseph D.; FOX, Alexa K., 2020. Rising with the Machines: A Sociotechnical Framework for Bringing Artificial Intelligence into the Organization. *Journal of Business Research* [online]. Vol. 120, pp. 262–273 [visited on 2025-05-27]. ISSN 0148-2963. Available from DOI: 10.1016/j.jbusres.2020.07.045.

MARIANI, Marcello; DWIVEDI, Yogesh K., 2024. Generative Artificial Intelligence in Innovation Management: A Preview of Future Research Developments. *Journal of Business Research* [online]. Vol. 175, p. 114542 [visited on 2025-01-03]. ISSN 0148-2963. Available from DOI: 10.1016/j.jbusres.2024.114542.

MCINERNEY, Claire, 2002. Knowledge Management and the Dynamic Nature of Knowledge. *Journal of the American Society for Information Science and Technology* [online]. Vol. 53, no. 12, pp. 1009–1018 [visited on 2024-12-20]. ISSN 1532-2890. Available from DOI: 10.1002/asi.10109.

METCALF, Gary S., 2024. An Introduction to Industry 5.0: History, Foundations, and Futures. In: NOUSALA, Susu; METCALF, Gary; ING, David (eds.). *Industry 4.0 to Industry 5.0: Explorations in the Transition from a Techno-economic to a Socio-technical Future* [online]. Singapore: Springer Nature, pp. 1–29 [visited on 2024-10-16]. Available from DOI: 10.1007/978-981-99-9730-5_1.

MODGIL, Sachin; GUPTA, Shivam; KAR, Arpan Kumar; TUUNANEN, Tuure, 2025. How Could Generative AI Support and Add Value to Non-Technology Companies – A Qualitative Study. *Technovation* [online]. Vol. 139, p. 103124 [visited on 2024-11-02]. ISSN 0166-4972. Available from DOI: 10.1016/j.technovation.2024.103124.

MOLINA, Arturo, 2023. Emerging Approaches for Enterprises and Human Integration Towards Industry 5.0. In: CAMARINHA-MATOS, Luis M.; BOUCHER, Xavier; ORTIZ, Angel (eds.). *Collaborative Networks in Digitalization and Society 5.0*. Cham: Springer Nature Switzerland, pp. 353–364. Available from DOI: 10.1007/978-3-031-42622-3_25.

NI, Bo; KAPLAN, David L.; BUEHLER, Markus J., 2023. Generative Design of *de Novo* Proteins Based on Secondary-Structure Constraints Using an Attention-Based Diffusion Model. *Chem* [online]. Vol. 9, no. 7, pp. 1828–1849 [visited on 2025-01-27]. ISSN 2451-9294. Available from DOI: 10.1016/j.chempr.2023.03.020.

NONAKA, I; TOYAMA, R; NAGATA, A, 2000. A Firm as a Knowledge-Creating Entity: A New Perspective on the Theory of the Firm. *Industrial and Corporate Change* [online]. Vol. 9, no. 1, pp. 1–20 [visited on 2025-01-14]. ISSN 0960-6491. Available from DOI: 10.1093/icc/9.1.1.

NONAKA, Ikujiro, 1994. A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*. Vol. 5, no. 1, pp. 14–37. Available from JSTOR: 2635068.

NONAKA, Ikujiro; TAKEUCHI, Hirotaka, 1995. *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford University Press.

OLIVEIRA, Arlindo, 2025. *A Inteligência Artificial Generative*. Fundação Francisco Manuel dos Santos.

PAYNE, Judy; FRYER, Jonathan, 2020. Knowledge Management and Information Management: A Tale of Two Siblings. *Business Information Review* [online]. Vol. 37, no. 2, pp. 69–77 [visited on 2024-10-16]. ISSN 0266-3821. Available from DOI: 10.1177/0266382120923971.

PEFFERS, Ken; TUUNANEN, Tuure; ROTHENBERGER, Marcus A.; CHATTERJEE, Samir, 2007. A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*. Vol. 24, no. 3, pp. 45–78. Available from DOI: 10.2753/MIS0742-1222240302.

PERMANA, Remi Indra; SUROSO, Jarot S., 2018. Data Governance Maturity Assessment at PT. XYZ. Case Study: Data Management Division. In: *2018 International Conference on Information Management and Technology (ICIMTech)* [online]. Jakarta: IEEE, pp. 15–20 [visited on 2025-02-20]. Available from DOI: 10.1109/ICIMTech.2018.8528142.

PICKARD, Alison Jane, 2013. *Research Methods in Information* [online]. Facet [visited on 2025-01-29]. Available from DOI: 10.29085/9781783300235.

POLANYI, Michael, 1958. *Personal Knowledge: Towards a Post-Critical Philosophy*. Ed. by NYE, Mary Jo. Chicago: University of Chicago Press.

POTTHOFF, Leonie; NAUSSEDAT, Rolf; GUNNEMANN, Lisa, 2024. Exploring Generative AI's Role in Manual Assembly: Application Potentials and Use Concepts. *Procedia CIRP* [online]. Vol. 130, pp. 194–199 [visited on 2025-05-15]. ISSN 2212-8271. Available from DOI: 10.1016/j.procir.2024.10.075.

PRASAD AGRAWAL, Kalyan, 2024. Towards Adoption of Generative AI in Organizational Settings. *Journal of Computer Information Systems* [online]. Vol. 64, no. 5, pp. 636–651 [visited on 2024-12-16]. ISSN 0887-4417. Available from DOI: 10.1080/08874417.2023.2240744.

PRZEGALINSKA, Aleksandra; TRIANTORO, Tamilla; KOVBASIUK, Anna; CIECHANOWSKI, Leon; FREEMAN, Richard B.; SOWA, Konrad, 2025. Collaborative AI in the Workplace: Enhancing Organizational Performance through Resource-Based and Task-Technology Fit Perspectives. *International Journal of Information Management* [online]. Vol. 81, p. 102853 [visited on 2024-12-16]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2024.102853.

RADFORD, Alec; NARASIMHAN, Karthik; SALIMANS, Tim; SUTSKEVER, Ilya, 2018. Improving Language Understanding by Generative Pre-Training.

RAJARAM, Kumaran; TINGUELY, Patrick Nicolas, 2024. Generative Artificial Intelligence in Small and Medium Enterprises: Navigating Its Promises and Challenges. *Business Horizons* [online]. Vol. 67, no. 5, pp. 629–648 [visited on 2025-05-26]. ISSN 0007-6813. Available from DOI: 10.1016/j.bushor.2024.05.008.

RAMAUL, Laavanya; RITALA, Paavo; RUOKONEN, Mika, 2024. Creational and Conversational AI Affordances: How the New Breed of Chatbots Is Revolutionizing Knowledge Industries. *Business Horizons* [online]. Vol. 67, no. 5, pp. 615–627 [visited on 2024-12-15]. ISSN 0007-6813. Available from DOI: 10.1016/j.bushor.2024.05.006.

RIEMER, Kai; PETER, Sandra, 2024. Conceptualizing Generative AI as Style Engines: Application Archetypes and Implications. *International Journal of Information Management* [online]. Vol. 79, p. 102824 [visited on 2024-12-16]. ISSN 0268-4012. Available from DOI: 10.1016/j.ijinfomgt.2024.102824.

ROWLEY, Jennifer, 1998. Towards a Framework for Information Management. *International Journal of Information Management* [online]. Vol. 18, no. 5, pp. 359–369 [visited on 2025-02-15]. ISSN 0268-4012. Available from DOI: 10.1016/S0268-4012(98)00025-5.

ROWLEY, Jennifer, 2007. The Wisdom Hierarchy: Representations of the DIKW Hierarchy. *Journal of Information Science* [online] [visited on 2025-06-11]. Available from: https://journals.sagepub.com/doi/10.1177/0165551506070706.

SABHERWAL, Rajiv; GROVER, Varun, 2024. The Societal Impacts of Generative Artificial Intelligence: A Balanced Perspective. *Journal of the Association for Information Systems*. Vol. 25, no. 1, pp. 13–22. ISSN 1536-9323. Available from DOI: 10.17705/1jais.00860.

SAI, Siva; SAI, Revant; CHAMOLA, Vinay, 2025a. Generative AI for Industry 5.0: Analyzing the Impact of ChatGPT, DALLE, and Other Models. *IEEE Open Journal of the Communications Society* [online]. Vol. 6, pp. 3056–3066 [visited on 2025-05-15]. ISSN 2644-125X. Available from DOI: 10.1109/OJCOMS.2024.3400161.

SAI, Siva; SAI, Revant; CHAMOLA, Vinay, 2025b. Generative AI for Industry 5.0: Analyzing the Impact of ChatGPT, DALLE, and Other Models. *IEEE Open Journal of the Communications Society* [online]. Vol. 6, pp. 3056–3066 [visited on 2025-06-19]. ISSN 2644-125X. Available from DOI: 10.1109/OJCOMS.2024.3400161.

SCHECTER, Aaron; RICHARDSON, Benjamin, 2025. How the Role of Generative AI Shapes Perceptions of Value in Human-AI Collaborative Work. In: *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* [online]. New York, NY, USA: Association for Computing Machinery, pp. 1–15 [visited on 2025-05-26]. CHI '25. Available from DOI: 10.1145/3706598.3713946.

SHAFIEE, Sara, 2025. Generative AI in Manufacturing: A Literature Review of Recent Applications and Future Prospects. *Procedia CIRP* [online]. Vol. 132, pp. 1–6 [visited on 2025-03-13]. ISSN 22128271. Available from DOI: 10.1016/j.procir.2025.01.001.

SHI, Yingnan; MA, Chao, 2024. Unravelling the Knowledge Matrix: Exploring Knowledge-Sharing Behaviours on Market-Based Platforms Using Regression Tree Analysis. *Personnel Review* [online]. Vol. 54, no. 1, pp. 284–308 [visited on 2025-05-16]. ISSN 0048-3486. Available from DOI: 10.1108/PR-01-2024-0052.

SIMON, Herbert A., 1996. *The Sciences of the Artificial, Third Edition*. MIT Press. ISBN 978-0-262-26449-5. Available from Google Books: k5Sr0nFw7psC.

SOARES, António Lucas; GOMES, Jorão; ZIMMERMANN, Ricardo; RHODES, Donna; DORNER, Verena, 2024. Integrating AI in Supply Chain Management: Using a Socio-Technical Chart to Navigate Unknown Transformations. In: CAMARINHA-MATOS, Luis M.; ORTIZ, Angel; BOUCHER, Xavier; BARTHE-DELANOË, Anne-Marie (eds.). *Navigating Unpredictability: Collaborative Networks in Non-linear Worlds*. Cham: Springer Nature Switzerland, pp. 22–35. Available from DOI: 10.1007/978-3-031-71739-0_2.

SONY, Michael; NAIK, Subhash, 2020. Industry 4.0 Integration with Socio-Technical Systems Theory: A Systematic Review and Proposed Theoretical Model. *Technology in Society* [online]. Vol. 61, p. 101248 [visited on 2025-06-13]. ISSN 0160-791X. Available from DOI: 10.1016/j.techsoc.2020.101248.

STOREY, Veda Catherine, 2025. Knowledge Management in a World of Generative AI: Impact and Implications. *ACM Transactions on Management Information Systems* [online], p. 3719209 [visited on 2025-03-06]. ISSN 2158-656X, ISSN 2158-6578. Available from DOI: 10.1145/3719209.

SUMBAL, Muhammad Saleem; AMBER, Quratulain, 2024. ChatGPT: A Game Changer for Knowledge Management in Organizations. *KYBERNETES* [online] [visited on 2024-12-20]. ISSN 0368-492X, ISSN 1758-7883. Available from DOI: 10.1108/K-06-2023-1126.

SUMBAL, Muhammad Saleem; AMBER, Quratulain; TARIQ, Adeel; RAZIQ, Muhammad Mustafa; TSUI, Eric, 2024. Wind of Change: How ChatGPT and Big Data Can Reshape the Knowledge Management Paradigm? *Industrial Management & Data Systems* [online]. Vol. 124, no. 9, pp. 2736–2757 [visited on 2024-11-25]. ISSN 0263-5577. Available from DOI: 10.1108/IMDS-06-2023-0360.

TAEIHAGH, Araz, 2025. Governance of Generative AI. *Policy and Society* [online], puaf001 [visited on 2025-03-20]. ISSN 1449-4035, ISSN 1839-3373. Available from DOI: 10.1093/polsoc/puaf001.

TAHERDOOST, Hamed; MADANCHIAN, Mitra, 2023. Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation. *Computers* [online]. Vol. 12, no. 4, p. 72 [visited on 2024-10-10]. ISSN 2073-431X. Available from DOI: 10.3390/computers12040072.

TAIWO, Ridwan; BELLO, Idris Temitope; ABDULAI, Sulemana Fatoama; YUSSIF, Abdul-Mugis; SALAMI, Babatunde Abiodun; SAKA, Abdullahi; ZAYED, Tarek, 2024. *Generative AI in the Construction Industry: A State-of-the-art Analysis* [online]. 2024-02-15. [visited on 2025-07-27]. Available from DOI: 10.48550/arXiv.2402.09939.

TEUBNER, Timm; FLATH, Christoph M.; WEINHARDT, Christof; van der AALST, Wil; HINZ, Oliver, 2023. Welcome to the Era of ChatGPT et Al. *Business & Information Systems Engineering* [online]. Vol. 65, no. 2, pp. 95–101 [visited on 2025-01-26]. ISSN 1867-0202. Available from DOI: 10.1007/s12599-023-00795-x.

THALHEIM, Bernhard, 2019. Conceptual Models and Their Foundations. In: SCHEWE, Klaus-Dieter; SINGH, Neeraj Kumar (eds.). *Model and Data Engineering*. Cham: Springer International Publishing, pp. 123–139. ISBN 978-3-030-32065-2. Available from DOI: 10.1007/978-3-030-32065-2_9.

TOORAJIPOUR, Reza; OGHAZI, Pejvak; PALMIÉ, Maximilian, 2024. Data Ecosystem Business Models: Value Propositions and Value Capture with Artificial Intelligence of Things. *International Journal of Information Management* [online]. Vol. 78, p. 102804 [visited on 2025-02-21]. ISSN 02684012. Available from DOI: 10.1016/j.ijinfomgt.2024.102804.

TUOMI, Ilkka, 1999. Data Is More than Knowledge: Implications of the Reversed Knowledge Hierarchy for Knowledge Management and Organizational Memory. *Journal of Management Information Systems* [online]. Vol. 16, no. 3, pp. 103–117 [visited on 2025-01-16]. ISSN 0742-1222. Available from DOI: 10.1080/07421222.1999.11518258.

VANCE, David, 1997. Information, Knowledge and Wisdom:The Epistemic Hierarchy andComputer-Based Information Systems. *AMCIS 1997 Proceedings*. Available also from: https://aisel.aisnet.org/amcis1997/165.

VUJOVIĆ, Dušan, 2024. Generative AI: Riding the New General Purpose Technology Storm. *Ekonomika preduzeca* [online]. Vol. 72, no. 1–2, pp. 125–136 [visited on 2024-11-18]. ISSN 0353-443X, ISSN 2406-1239. Available from DOI: 10.5937/EKOPRE2402125V.

WASCHULL, Sabine; EMMANOUILIDIS, Christos, 2023. Assessing Human-Centricity in AI Enabled Manufacturing Systems: A Socio-Technical Evaluation Methodology. *IFAC-PapersOnLine* [online]. Vol. 56, no. 2, pp. 1791–1796 [visited on 2024-08-13]. ISSN 2405-8963. Available from DOI: 10.1016/j.ifacol.2023.10.1891.

WEI, Xiahua; KUMAR, Naveen; ZHANG, Han, 2025. Addressing Bias in Generative AI: Challenges and Research Opportunities in Information Management. *Information & Management* [online]. Vol. 62, no. 2, p. 104103 [visited on 2025-06-06]. ISSN 0378-7206. Available from DOI: 10.1016/j.im.2025.104103.

WIIG, Karl M., 1997. Knowledge Management: Where Did It Come from and Where Will It Go? *Expert Systems with Applications* [online]. Vol. 13, no. 1, pp. 1–14 [visited on 2024-12-20]. ISSN 0957-4174. Available from DOI: 10.1016/S0957-4174(97)00018-3.

WILSON, T. D., 2011. Information Management Today and Tomorrow [online] [visited on 2024-12-02]. Available from: https://www.informationr.net/tdw/publ/papers/2011MurciaIMWkshop.html.

WOODRUFF, A.; SHELBY, R.; KELLEY, P.G.; ROUSSO-SCHINDLER, S.; SMITH-LOUD, J.; WILCOX, L., 2024. How Knowledge Workers Think Generative AI Will (Not) Transform Their Industries. In: available from DOI: 10.1145/3613904.3642700.

XU, Qingfeng; ZHOU, Guanghui; ZHANG, Chao; CHANG, Fengtian; CAO, Yan; ZHAO, Dan, 2024. Generative AI and DT Integrated Intelligent Process Planning: A Conceptual Framework. *The International Journal of Advanced Manufacturing Technology* [online]. Vol. 133, no. 5, pp. 2461–2485 [visited on 2025-06-12]. ISSN 1433-3015. Available from DOI: 10.1007/s00170-024-13861-9.

YU, Xinying; XU, Shi; ASHTON, Mark, 2022. Antecedents and Outcomes of Artificial Intelligence Adoption and Application in the Workplace: The Socio-Technical System Theory Perspective. *Information Technology & People* [online]. Vol. 36, no. 1, pp. 454–474 [visited on 2024-08-13]. ISSN 0959-3845. Available from DOI: 10.1108/ITP-04-2021-0254.

ZHANG, Caiming; ZHANG, Hui, 2025. The Impact of Generative AI on Management Innovation. *Journal of Industrial Information Integration* [online]. Vol. 44, p. 100767 [visited on 2025-03-13]. ISSN 2452414X. Available from DOI: 10.1016/j.jii.2024.100767.

ZHANG, Qichao; ZUO, Jiaxiang; YANG, Songlin, 2025. Research on the Impact of Generative Artificial Intelligence (GenAI) on Enterprise Innovation Performance: A Knowledge Management Perspective. *Journal of Knowledge Management* [online] [visited on 2025-04-29]. ISSN 1367-3270, ISSN 1758-7484. Available from DOI: 10.1108/JKM-10-2024-1198.

ZHANG, Wenyao; ZHANG, Wei; DAIM, Tugrul; YALÇIN, Haydar, 2025. AI Challenges Conventional Knowledge Management: Light the Way for Reframing SECI Model and Ba Theory. *Journal of Knowledge Management* [online]. Vol. 29, no. 5, pp. 1618–1654 [visited on 2025-05-16]. ISSN 1758-7484. Available from DOI: 10.1108/JKM-02-2024-0203.

ZHANG, Zhijun; ZHANG, Jian; ZHANG, Xiaodong; MAI, Weijian, 2025. A Comprehensive Overview of Generative AI (GAI): Technologies, Applications, and Challenges. *Neurocomputing* [online]. Vol. 632, p. 129645 [visited on 2025-03-13]. ISSN 09252312. Available from DOI: 10.1016/j.neucom.2025.129645.

Appendix A

Appendix 1

In this appendix, it is presented the document that was shared with the participants to inform them about the context, objectives, agenda, and questions.

Focus Group: Framework Evaluation and Validation

Objective

To evaluate the relevance, clarity, theoretical accuracy, and applicability of the Generative AI-Enhanced Knowledge Management Framework (GAKMF) developed in the dissertation entitled *"The Impacts of Generative AI on Knowledge Management Processes within Organizations"*, gathering insights from professionals with expertise in Knowledge Management, Information Management, Data Management and Governance, and Artificial Intelligence (GenAI).

Framework Objective – Summary for Participants

The Generative AI-Enhanced Knowledge Management Framework (GAKMF) was developed to guide organizations in the strategic and responsible adoption of GenAI to enhance knowledge management processes. Recognizing that GenAI can profoundly impact how knowledge is created, stored and retrieved, transferred, and shared, the framework integrates organizational, technical, ethical, and sociotechnical dimensions.

The framework's objectives are:

- Map the relationships between all the disciplines that work as enablers of GenAI adoption and implementation: Information Management, Data Management, Data Governance, and Knowledge Management.
- Emphasize the importance of strategic alignment, data and ethical readiness, and sociotechnical integration.
- Offer a structured model to help organizations leverage GenAI in a way that is effective, responsible, and contextually adaptable to improve organizational performance.

Structure of the Session

- **Duration:** 50–75 minutes
- **Format:** In-person and remote (MS Teams)
- **Meeting Room:** 1 Andar B1.1 – CESE – INESC TEC – Institute for Systems and Computer Engineering, Technology and Science
- **Online Room:** [To be defined]
- **Participants:** 4–6
- **Methodology:** Semi-structured group discussion with a guided moderator script and a visual presentation of the GAKMF framework.

Agenda

Time	**Segment**	**Description**
5–10 minutes	Welcome and objectives	Explanation of the purpose of the session and objectives
5–10 minutes	Presentation of GAKMF	Presentation of the framework (Figure 1). Highlight of each layer (Organizational Strategy, Data Preparation, Sociotechnical, KM processes–GenAI, Expected Results)
35–45 minutes	Guided discussion	Exploration of participants' views by focused questions
5–10 minutes	Wrap-up	Summarization of key points. Final suggestions. Thank participants

Discussion Questions

1. Is the GAKMF framework clearly structured and easy to understand? Is the "narrative" of the framework — considering the relationships and interacting of disciplines — understandable?

   - Is the framework aligned with the intended purpose of the dissertation?
   - Were all aspects of taken into consideration? As an example, knowledge is not represented just like data and information is (in the middle of data management and data governance). Should knowledge be considered in this framework?
     If yes: where?
   - Do you think this framework can be contextually adapted to different types of organizations?
     If no: what needs to be improved?

2. In relation to the representation of Information Management, how important the specification of IM processes are in this context?

3. How meaningful is the relationship “supports” between “Organization Strategic Definition” and the GenAI system?

4. Considering the level “Data and Ethical Preparation”, does the framework adequately reflect the importance of high-quality, well-structured, and accessible data as a prerequisite of GenAI-driven KM processes?

    - In your opinion, what aspects of data readiness are most often underestimated in practice?
    - Are any key dimensions of data quality missing or misrepresented?

5. In your opinion, is there any aspect or perspective (e.g. risks and challenges) that must be represented in the Data Governance and Management from the “Data and Ethical Preparation” level?

6. Much of the current research on Generative AI tends to adopt a technocentric perspective, often neglecting the social, organizational, and human dimensions that shape its implementation and impact. This framework explicitly includes a sociotechnical layer to reflect the importance of the interaction between social systems and technical systems. In your view, is this sociotechnical alignment meaningfully represented in the framework?

    - Is the social and technical system implemented correctly? Is there another organization that is easier to comprehend how GenAI operates within them?
    - What are the aspects that should be included in the technical system considering the context of the framework?
    - In your opinion, where should be included the human-feedback loop in the framework? Is it well-positioned between the social system and the GenAI system? What about the technical system? Is it necessary?
    - Is the relationship between knowledge management processes, the social and technical system — “is part of” — understandable and meaningful?
    - What is your opinion about the position of the GenAI system in the middle of the sociotechnical systems (social and technical)? Is it understandable within the context?

7. In your opinion, does the “GenAI system” layer of the framework sufficiently represent the core capabilities and functionalities of current Generative AI technologies? Are they understandable?

    - Are any key capabilities missing or misrepresented?

8. In relation to the KM processes enhanced by GenAI, how would rank the depth or superficiality of the impact attributed from GenAI in each KM process? What kind of adjustments can be made in terms of usefulness for the organizations?

9. How useful would this framework be for an organizational context that desires to implement GenAI to enhance KM processes?

   - How would you rank the usefulness of the framework levels in terms of importance for the design and development of GenAI within organizations?
   - What aspects should be considered and reiterated?
   - Would you recommend clarifying or expanding the technical architecture elements of the technology in the framework?

10. In your opinion, would you change the level of abstraction of the framework? Is it preferable a high or low-level description for this framework? In what aspects?

11. In your opinion, attending your organizational and/or technical experience, what other aspects should be covered in the framework? Is any aspect on a specific level that should be introduced?