Rethinking Knowledge Creation in the age of Digital Innovation: Insights from IT Sector

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Abstract: Recent literature highlights that generative artificial intelligence (GenAI) is expected to play a central role in knowledge-intensive work, particularly in sectors strongly exposed to technological innovation. Beyond facilitating existing knowledge management (KM) practices, GenAI appears to introduce a fundamentally new epistemic dimension that challenges traditional models of organizational knowledge creation, most notably Nonaka's SECI model. While the SECI framework has long explained knowledge creation through the dynamic interaction between tacit and explicit human knowledge, it does not explicitly account for knowledge processes emerging from human-AI interaction. Drawing on these premises, the aim of this research is to investigate how GenAI alters knowledge creation dynamics and to identify new knowledge conversion mechanisms emerging from human-machine interaction. To achieve this, the study adopts an exploratory single case study within the IT sector, an environment characterized by high innovation intensity and rapid technological change. The selected case organization was chosen based on its positioning along three key dimensions known to influence technology adoption: orientation to innovation, technological culture and organizational complexity. Data were collected over a period of one year and five months through thirty semi-structured interviews with employees across R&D, operations and senior management. Data were triangulated by direct observation and analysis of project documentation. The qualitative data were analysed using content analysis supported by inductive coding techniques inspired by grounded theory. This process led to the construction of an inductive coding tree capturing core themes and their relationships. Findings reveal that GenAI generates knowledge dynamics that cannot be fully mapped onto the traditional model. In particular, new knowledge conversion modes emerge between human knowledge, machine-generated data and artificial knowledge. These include transformations from human tacit and explicit knowledge into data, from data into artificial knowledge and from artificial knowledge back into human explicit knowledge. Alongside these conversion modes, several conceptual domains were identified. Based on these results, the study proposes a novel conceptual framework that integrates the SECI model with a machine dimension, offering a more comprehensive representation of contemporary knowledge creation in organizations which integrate GenAI into their processes. The framework highlights the importance of strategic integration of GenAI into KM processes and the value of human-in-the-loop validation. This research contributes to KM theory by extending classical models to account for artificial knowledge generation and provides a foundation for future empirical studies on human-machine knowledge ecosystems.

Keywords: Artificial intelligence (AI), Artificial knowledge management (AKM), Artificial knowledge generation, SECI, Generative artificial Intelligence (GenAI), DIKW hierarchy

1. Introduction

Generative Artificial Intelligence (GenAI) has demonstrated significant potential to enhance human productivity and support complex cognitive tasks, as it is capable of autonomously generating new forms of content by identifying patterns within large volumes of previously available data. Owing to these capabilities, increasing attention has been directed toward this technology by both public and private organizations (Zhang et al., 2025). Consequently, substantial investments are currently being made by many firms to develop and integrate GenAI solutions into their operational processes. According to recent studies, the widespread diffusion of GenAI is expected to produce considerable transformations for both individuals and organizations in the coming years, even in situations where its formal adoption remains limited (Albashrawi, 2025). Within this evolving landscape, a major challenge for managers will consist in understanding how GenAI affects organizational activities, particularly those related to decision-making processes and knowledge-intensive work. In such a context, knowledge management (KM) assumes a particularly relevant role. KM refers to the set of processes through which knowledge is collected, shared and created within organizations in order to effectively leverage available informational resources. When properly structured, KM practices enable organizations to enhance operational efficiency while simultaneously strengthening their capacity for innovation. To explain how knowledge is generated and circulated within organizations, several established theoretical frameworks have been developed. Among the most influential are the Absorptive Capacity Model, the Organizational Learning Model (Crossan et al., 1999), and Nonaka's SECI model (Nonaka, 1994). These frameworks have provided organizations with valuable conceptual foundations for structuring knowledge processes and maximizing the strategic value of their knowledge assets. Among them, the SECI model, by explicitly describing the dynamic interaction between tacit and explicit knowledge in knowledge creation, appears to provide a particularly suitable lens through which to analyse the integration of GenAI from an organizational knowledge creation perspective.

Specifically, previous studies have begun to examine the relationship between GenAI and knowledge creation from two complementary perspectives. First, research has explored how GenAI influences the different phases of the SECI model, highlighting its potential impact on traditional knowledge conversion processes (Liccardo and Cerchione, 2025). Second, recent studies have acknowledged the existence of a machine dimension in organizational knowledge creation (Cerchione et al., 2026). However, the specific mechanisms through which human tacit and explicit knowledge interact with data and artificial knowledge remain underexplored. This study addresses this gap by empirically identifying and systematizing knowledge conversion modes emerging from human-GenAI interaction within organizational workflows. To reach this objective, the present study develops an integrated conceptual framework that captures these interactions and contributes to a deeper understanding of GenAI-enabled knowledge creation. In doing so, the research seeks to stimulate further discussion on the role of GenAI in knowledge management and to provide a systematic foundation for future studies in this field.

2. Theoretical Background

The growing body of literature addressing the use of GenAI in organizational contexts highlights its transformative implications from a knowledge management perspective. In particular, previous studies suggest that GenAI has significant potential to influence the acquisition, dissemination and creation of knowledge within organizations (A Mooradian, 2024). However, interpreting GenAI solely as an auxiliary tool supporting existing knowledge management practices may represent an overly limited perspective. Rather than simply enhancing traditional processes, GenAI appears to introduce a new dimension within knowledge generation (Figure 1).

Scholarly work increasingly suggests that organizational knowledge creation may involve the interaction of two distinct yet interconnected dimensions. The first is the human dimension, which encompasses conventional knowledge creation processes and has been extensively conceptualized within the literature, most notably in the work of Nonaka (Nonaka, 1994). Alongside this, a machine dimension can be identified, enabling new forms of human-machine and machine-machine interactions that contribute to the emergence of novel knowledge.

While the human-centered processes described by Nonaka (1994) have been widely studied, a structured framework for understanding knowledge generation within the machine domain remains largely underdeveloped. For this reason, the present study adopts an exploratory case study approach to investigate the fundamental relationships between the human and machine dimensions. In doing so, it seeks to further examine a concept that Nonaka and Toyama (2003) had already suggested, but which has remained conceptually ambiguous in light of the recent emergence of GenAI technologies.

Within the machine dimension, data represents the fundamental component enabling knowledge-related processes. The ability of GenAI systems to autonomously generate new content is largely dependent on the extensive datasets from which they learn and upon which they perform analysis. In general terms, data can be described as symbols representing the properties of objects, as well as factual recordings or measurements used as the basis for reasoning and computation (Rowley, 2007). Consequently, both the quantity and the quality of available data significantly influence the performance of GenAI models. For this reason, effective data management and governance become essential for unlocking the full potential of GenAI technologies, in a way that is comparable to how the richness of human experience contributes to the development of human knowledge. From a cognitive perspective, human reasoning is often supported by the construction and manipulation of analogies based on mental models, structured representations of reality that guide interpretation, reasoning and decision-making (Johnson-Laird, 1995). A similar logic can be extended to machines, which process large volumes of data through algorithmic systems in order to generate new outputs. In this sense, the “mental models” of machines may be understood as structured combinations of data and computational processes, such as those implemented in foundation models and deep learning architectures. Over time, the machine dimension has evolved beyond its traditional role as a simple data repository, increasingly performing functions related to data processing, pattern recognition and automated decision support. This evolution raises an important question regarding whether the outputs produced by such systems can be considered a distinct form of knowledge, often referred to as artificial knowledge. Conceptualizing artificial knowledge, however, remains challenging, as even traditional human knowledge is widely recognized as a complex and multifaceted construct. Some contributions in the literature suggest that machines may already possess a form of knowledge, particularly what has been described as actionable knowledge, referring to the practical use of information for solving specific problems (Jashapara, 2004). Nevertheless, further research is required to determine whether machines are capable of developing deeper conceptual forms of knowledge comparable to those produced through human cognition. Based on these considerations, it may be argued that machines are currently able to process and utilize information in ways that resemble the human use of actionable knowledge. However, the extent to which machines can engage in genuine conceptual reasoning remains an open question that lies beyond the scope of the present study.

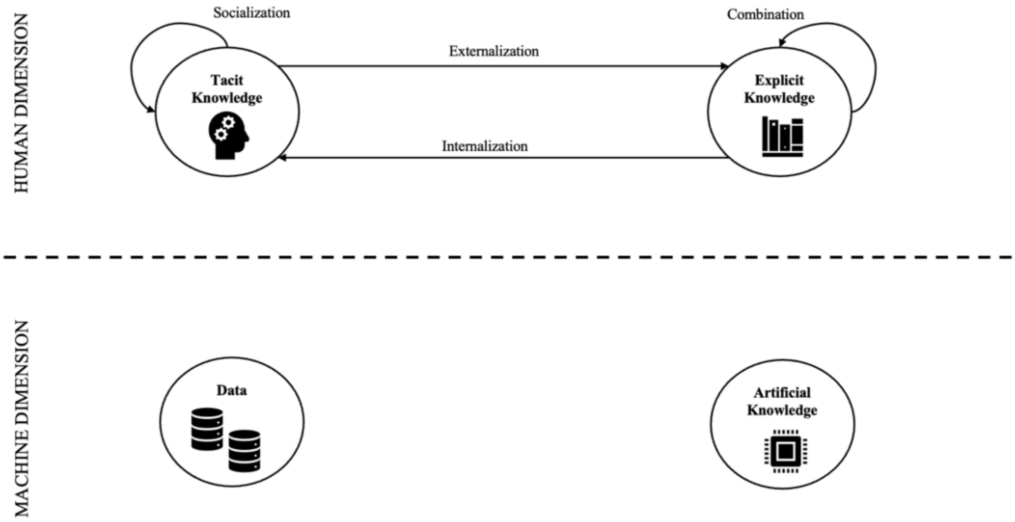

Figure 1: Human and Machine dimension

3. Methodology

The empirical investigation focuses on a single organization, in line with the logic of exploratory case study research (Ridder, 2017). The selected company is a small enterprise operating in the cybersecurity sector, providing services ranging from cybersecurity solutions to customized software development. The case was purposefully chosen based on its positioning across three key factors widely recognized as influencing the adoption of new technologies within firms (Teece, 2007): a) orientation toward innovation, b) prior technological culture and c) organizational complexity. These dimensions have been extensively discussed in the literature as critical determinants of a firm's openness to technological change, making the selected organization particularly suitable for investigating the integration of GenAI into operational processes. Building on this premise, the study was designed as an exploratory single case study. Following Ridder (2017), a case study was adopted to investigate GenAI integration into organizational workflows, analysing their implications beyond the knowledge creation processes described by Nonaka's SECI model. Data collection relied primarily on qualitative methods. The main sources included in-depth interviews with company employees and field notes gathered during a direct observation period lasting one year and five months. In addition, secondary materials, such as the company website and internal project documentation, were used to triangulate the empirical evidence (Yin, 2014). In total, thirty semi-structured interviews were conducted at different stages of the observation period. Participants occupied key roles within the R&D and operations departments, as well as within the senior management team, thus covering a broad spectrum of professional experience, from junior developers to senior managers. All interviews were audio-recorded and subsequently transcribed to ensure accuracy and completeness of the dataset. For data analysis, content analysis was adopted as the primary methodological approach (Bryman and Burgess, 1994), as it enables the systematic examination of complex phenomena through structured coding procedures (Saldaña, 2013). To support the development of inductive categories, coding techniques inspired by grounded theory were employed. The analysis began with a detailed examination of interview transcripts, which were subsequently organized using specialized qualitative analysis software. Data collection continued until theoretical saturation was reached, namely when additional interviews no longer generated substantially new codes or conceptual categories. An inductive coding tree was then developed, combining in vivo codes, which captured participants' original expressions, with researcher-generated descriptive codes derived from analytical interpretation. Through an iterative process, codes were progressively refined and validated through triangulation across interviews, field observations and internal documentation. Finally, codes were systematically compared and grouped into higher-order themes and overarching conceptual domains (CDs).

4. Results

Through an inductive coding process, several higher-level conceptual domains (CDs) were identified. These domains aggregate related themes emerging from the empirical data and represent broader analytical dimensions that characterize how GenAI reshapes knowledge creation processes within organizations. In particular, they highlight mechanisms and dynamics that cannot be fully explained by the traditional SECI phases alone, thus providing additional insights into the evolving relationship between human and machine dimensions in knowledge generation.

CD1: Data synthesis

The findings (Figure 2) indicate that the generation of synthetic data represents a significant advantage for organizations, provided that data validity is ensured and potential biases are effectively controlled. In the context of cybersecurity, the use of GenAI offers particularly valuable opportunities, especially through its capacity to create synthetic datasets for testing and experimentation purposes. As highlighted by a senior developer, "Generating synthetic data allows us to conduct in-depth analyses on the algorithms that form the core of new services".

Within the case study organization, this potential is supported by the implementation of rigorous validation protocols, which involve multiple stages of human oversight. As one participant emphasized, "Careful human supervision is essential to effectively mitigate bias and discrimination". In addition, specific privacy filters are applied to ensure compliance with regulatory requirements, as "data is shared only after all necessary measures have been implemented to guarantee privacy protection". Overall, the adoption of structured strategies for synthetic data generation appears to be crucial for fully leveraging its benefits. Such approaches enable organizations to access large volumes of specialized data that would otherwise be difficult to obtain, while maintaining control over data quality, ethical considerations and regulatory constraints.

1st order codes ("in vivo and descriptive coding)	*2nd order themes*	*Conceptual domains (CD)*
Providing alternative approaches and solutions in development *new data synthesis to produce new services* *test software functioning via synthetic data*	*Application of synthetic data*	*Data synthesis*
Synthetic data production and elaboration *Software development production* *Data analysis* *R&D tool* *Assisting in the generation and validation of synthetic data*	*Synthetic data generation*	
Human validation on a subset of data *"Using privacy filters"* *"Random sample validation"* *"Protocol to autonomously check the data produced"*	*Validation and filtering of synthetic data*	

Figure 2: Coding tree for "Data synthesis" conceptual domain

CD2: GenAI as innovation catalyst

The findings from the case study (Figure 3) confirm the strong potential of GenAI to act as both a driver of innovation and a source of productivity enhancement. By enabling the generation of original content and the aggregation of fragmented information, GenAI contributes to accelerating innovation cycles and fostering a more creativity-oriented organizational environment. In this sense, it supports not only idea generation but also the development of a broader innovation culture. In addition to its impact on creativity, GenAI plays a significant role in workflow automation and process optimization, leading to tangible productivity improvements, particularly in software development contexts. Its contribution also extends to managerial activities, where it supports tasks such as project planning and resource allocation. As one manager noted, "GenAI helps me in GNATT scheduling activities". However, the evidence suggests that these benefits are not automatically realized. Their full potential depends on the organization's ability to actively and strategically integrate GenAI into existing workflows. As emphasized by a senior team member, "effectively integrating GenAI in workflow processes is the key, the risk is to be passively affected by this revolution." This perspective was consistently reinforced by multiple managers and senior professionals, highlighting the importance of a deliberate and structured approach to GenAI adoption.

1st order codes ("in vivo and descriptive coding)	*2nd order themes*	*Conceptual domains (CD)*
"GenAI is a colleague in code production" *Human-machine new insight generation* *Learning path discovery* *Service optimization via simulation*	*collaboration with GenAI*	*GenAI as innovation catalyst*
Increase learning speed *Innovation catalyst* *"Promoting an innovation-oriented ambience"*	*driving organizational innovation*	
"Communicating operational results" *Accelerating software development through AI-generated code suggestions* *Organizational process optimization* *Improving communication* *Improving productivity* *Proactive integration* *Internal process optimization*	*increase in productivity and workflow optimization*	

Figure 3: Coding tree for "GenAI as innovation catalyst" conceptual domain

CD3: GenAI new insights

GenAI has demonstrated a strong capability to identify hidden patterns and connections within large and complex datasets, making it particularly valuable in domains that rely on advanced data analysis. By enabling the detection of relationships that might otherwise remain unnoticed, it supports more informed and insightful decision-making. As one participant observed, "GenAI allows you to notice some elements that you may overlook". Within the case study organization, this potential is applied to tasks such as detecting anomalous patterns, mapping network traffic, and uncovering previously unrecognized links between security threats (Figure 4). When integrated responsibly into operational processes, these capabilities contribute to enhancing the overall value of the services delivered, particularly by strengthening proactive defence mechanisms against cyber threats.

1st order codes ("in vivo" and descriptive coding)	*2nd order themes*	*Conceptual domains (CD)*
Highlighting connection that were not evident *Putting in evidence new elements* *"Finding the link between phenomena"*	*identify hidden connections*	*GenAI new insights*
New feature extraction *"Mapping traffic and anomaly detection"*	*Pattern recognition*	

Figure 4: Coding tree for "GenAI new insights" conceptual domain

CD4: Human role in GenAI-assisted workflows

The case study confirms that ethical considerations and human oversight remain central in GenAI-assisted workflows (Figure 5). Despite being an early adopter of these technologies, the organization has implemented a range of practices to ensure their responsible use. These include both simple measures, such as anticipating outputs and ensuring proper understanding of results, and more structured approaches, such as periodic compliance audits, described by one participant as "strict protocols that include periodic audits for data monitoring and control." Additional practices involve validation procedures, prompt engineering, "good answers mainly depend on good prompts", and the use of explainable AI (XAI) techniques. Across the organization, a strong emphasis is placed on critically reviewing GenAI outputs. As highlighted by the technical director, users are expected to actively interpret and validate results rather than passively accept them, recognizing that outputs are not error-free and must be carefully analysed. This need for oversight is particularly relevant in the cybersecurity domain, where strict data protection and privacy requirements make human validation indispensable. Moreover, current GenAI systems still present limitations, including overly simplified responses and the risk of hallucinations, which further reinforce the importance of human intervention. To address these challenges, the organization adopts a set of mitigation strategies aimed at balancing automation with human control. These include testing GenAI in synthetic scenarios, promoting prompt-sharing practices to enhance user capabilities, and providing structured training on both model functioning and validation procedures. As one employee noted, "I participate in training sessions organized by the company, where both the functioning of the models used and the procedures for validating the obtained results are explained". Overall, the findings suggest that the effective use of GenAI depends on fostering a critical mindset among employees, where outputs are not treated as definitive truths but as inputs to be actively evaluated and refined.

1st order codes ("in vivo and descriptive coding)	2nd order themes	Conceptual domains (CD)
low-biased algorithm use Balancing AI-generated insights with human judgment "Explaining results in formation sessions" Respecting privacy policy Responsibility in using GenAI outputs	Ethical use	Human role in GenAI-assisted workflows
Human revision for critical data Periodical conformity audit Having an expected output in advance Bias management "Correct use of the prompt engineering" "human supervision is still necessary due to the hallucinations and complex task resolution"	Human supervision	
"Integration mediated by actors' comprehension" Testing GenAI on synthetic scenario first Informal and formal best practice in using GenAI Explaining the functioning of the models Dealing with policy regulations XAI Critical thinking preservation GenAI hallucinations in answering Impossibility to completely substitute human interactions	Managing risk of using GenAI	

Figure 5: Coding tree for "Human role in GenAI-assisted workflows" conceptual domain

CD5: Risks associated with GenAI misuse

Despite its advantages, the use of GenAI also introduces significant risks, particularly those related to excessive dependence and the potential erosion of human capabilities (Figure 6). The findings suggest that employees may increasingly rely on AI-generated content, leading to a "loss of capacity to elaborate data from their own". This risk appears to be especially pronounced among less experienced professionals, who may attempt to compensate for knowledge gaps by relying heavily on GenAI, potentially bypassing essential learning processes. As a result, there is concern that the habitual use of AI for immediate solutions may reduce opportunities to "emulate the best ones", ultimately hindering the development of professional expertise over time. However, these risks are not limited to junior employees. More experienced professionals and managers may also be affected, as the automation of complex cognitive tasks can diminish their competitive advantage, or what one participant described as "working power". Over time, an overreliance on GenAI in decision-making processes may weaken critical thinking and creative problem-solving abilities. More broadly, the evidence points to a transformation in traditional experiential learning dynamics. In particular, younger professionals may face increasing difficulties in developing independent analytical skills. Additionally, uncritical reliance on GenAI outputs can lead users to "lose focus and explore wrong alternatives", resulting in inefficient use of time and resources. To mitigate these risks, organizations need to actively integrate GenAI into both operational workflows and employee training programs, ensuring that it functions as an augmentation tool rather than a substitute for human expertise. Equally important is the establishment of clear guidelines for responsible AI use, fostering a balanced approach that combines technological support with human judgment.

1st order codes ("in vivo" and descriptive coding)	2nd order themes	Conceptual domains (CD)
Decrease in the process of emulating the best Excessive dependence from this tech	dependence	Risks associated with GenAI misuse
the most skilled are the most in danger to lose their competitive advantages. Preventing knowledge stagnation by fostering independent thinking Avoiding excessive AI dependence in problem-solving Poor control on the use of GenAI	loss of skill	
Lack of deep context Strongly dependant from prompt Difficulties in using it to share knowledge Frequent hallucinations	issue on output	

Figure 6: Coding tree for "risk associated with GenAI misuse" conceptual domain

5. Discussion

Within these conceptual domains, several potential knowledge conversion modes (CMs) emerged from the empirical analysis. These conversion modes represent specific mechanisms through which knowledge is transformed across the human and machine dimensions. While the conceptual domains capture broader thematic areas describing how GenAI reshapes organizational knowledge practices, the conversion modes provide a more granular perspective on how knowledge flows and transformations occur between humans, data and AI systems. In this sense, the identified CMs extend the traditional SECI knowledge conversion logic by incorporating new forms of interaction involving human and machine dimensions. To provide a comprehensive overview, a conceptual framework was produced (Figure 7).

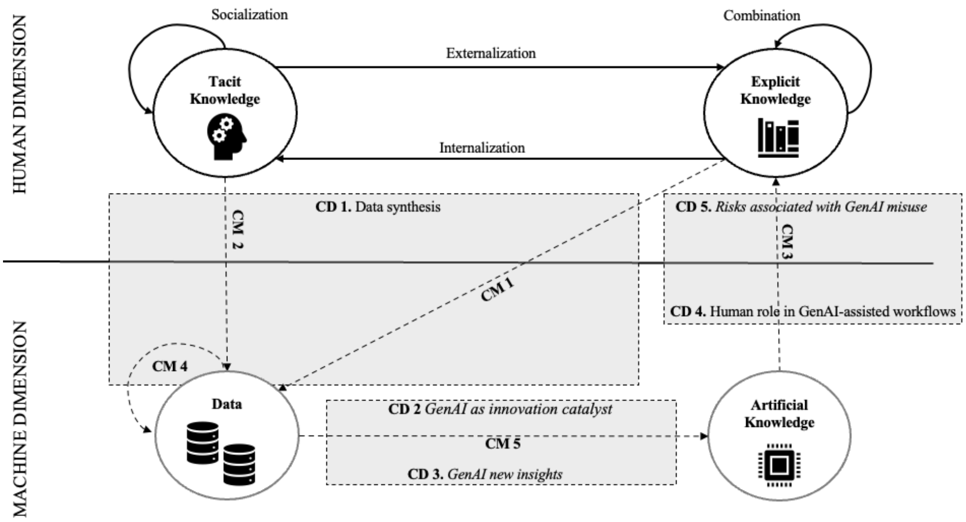

Figure 7: GenAI integrated framework

The empirical findings reveal several knowledge conversion dynamics that describe how human and machine dimensions interact within AI-mediated knowledge processes. These dynamics can be interpreted as a set of conversion modes that connect the elements of the human dimension (tacit and explicit knowledge) with those of the machine dimension (data and artificial knowledge). Each conversion mode emerges from specific conceptual domains identified in the coding process and highlights different mechanisms through which knowledge is transformed across human and machine actors. More specifically, the conversion modes emerged as analytical abstractions linking recurring empirical patterns observed across interviews, field observations and project documentation.

A first conversion dynamic emerged from the conceptual domain related to data synthesis and concerns the transformation of explicit human knowledge into machine-processable data (CM1). In this process, human actors play a crucial role in translating structured knowledge, such as documentation, guidelines or technical procedures, into datasets that can be used to train AI systems. For this transformation to be effective, data must accurately represent the complexity of real-world contexts and must be carefully filtered and validated before being used for training purposes. Within the case study organization, this process was particularly evident in the development of internal security policies and algorithmic specifications for GenAI applications. Through this approach, explicit organizational knowledge contained in technical documentation was intentionally converted into machine-readable data, providing a reliable foundation for AI training and strengthening trust in AI-assisted workflows. The same conceptual domain of data synthesis also revealed a second conversion dynamic involving the transformation of tacit human knowledge into data (CM2). Existing research suggests that tacit knowledge can be partially externalized through digital traces such as audio recordings, video material or textual artefacts. The findings of this study extend this perspective by highlighting how AI systems can learn from human-generated outputs even when these artefacts were not originally produced for the purpose of AI training. In practice, AI models analyse large volumes of human-produced material to detect recurring patterns embedded in everyday activities. These patterns may include linguistic structures extracted from written communication, visual cues derived from images or videos, and decision-making behaviours inferred from historical records of professional activity. The learning process therefore becomes continuous and dynamic, integrating heterogeneous data sources such as digital documentation, social media content and interactions captured through Internet of Things (IoT) devices. A major challenge associated with this conversion dynamic lies in the design of algorithms capable of identifying meaningful patterns while filtering out noise, errors and biases embedded in the source data. If not properly addressed, these biases may be reproduced or amplified by AI systems. For this reason, organizations must complement algorithmic design with clear internal guidelines regulating how employees interact with AI technologies. As one R&D manager explained, "internally validated best practices on how to interact with AI systems are the key for an ethical and responsible use of this powerful tool." A concrete example of this mechanism emerged from the analysis of developers' historical coding practices and interaction logs. Although these behaviours were not originally produced for AI training purposes, GenAI systems were able to identify recurring problem-solving strategies from source code repositories and development histories, effectively transforming tacit human expertise into structured data. These observations were grouped under themes related to behavioural trace extraction and pattern formalization, which informed the conceptualization of CM2. Another relevant conversion dynamic emerged from the conceptual domain related to ethics and the human role in GenAI-assisted workflows and concerns the transformation of artificial knowledge into explicit human knowledge (CM3). This finding is consistent with recent work emphasizing the importance of human oversight in AI-assisted decision processes, while extending these contributions by framing interpretability as a knowledge conversion mechanism enabler. GenAI systems rely heavily on deep learning architectures that often operate as complex “black boxes”. Unlike traditional machine learning techniques, whose decision rules can sometimes be partially interpreted, deep learning models provide limited transparency regarding how outputs are generated. For this reason, translating AI-generated outputs into forms that can be understood and interpreted by human actors becomes essential. In other words, artificial knowledge must be converted into explicit human knowledge that can inform responsible decision-making. This issue has become increasingly relevant across multiple domains, including education, healthcare and finance. In this context, Explainable Artificial Intelligence (XAI) techniques play a key role in increasing the transparency of AI systems by clarifying the rationale behind predictions, recommendations and classifications. By making AI outputs more interpretable, these approaches contribute to building trust, strengthening accountability and enabling responsible adoption of AI technologies in knowledge-intensive environments.

A further conversion dynamic, again linked to the conceptual domain of data synthesis, describes the transformation of explicit artificial knowledge into new data. In this stage, AI systems begin to assume a more proactive role in the knowledge creation process (CM4). Generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are capable of producing synthetic datasets that can subsequently be used for additional training and experimentation. As one senior R&D member explained, “we use variational models to generate and validate synthetic data. These datasets are part of a dynamic and cyclical process. The intentional disturbance allows the data to be reintroduced into the system for further learning.” Through this mechanism, the knowledge embedded in trained models is transformed into new data that feeds further learning cycles. This process represents an important step in the evolution of AI systems, shifting their role from purely human-operated tools to increasingly autonomous contributors to knowledge generation. Nevertheless, greater autonomy also raises important challenges. The creation and reuse of synthetic datasets require rigorous validation procedures to ensure data reliability, prevent the propagation of errors and avoid ethical issues such as bias amplification. Consequently, human oversight remains a crucial element of this stage, particularly in validating both AI-generated inputs and outputs.

Finally, a conversion dynamic emerging from the conceptual domain of GenAI-driven insights concerns the transformation of data into artificial knowledge (CM5). This mechanism represents one of the central motivations of the present study, as it illustrates the capacity of AI systems to generate new knowledge from large datasets. By leveraging foundation models and deep learning algorithms, AI systems can process vast quantities of structured and unstructured data to identify patterns, correlations and anomalies that may not be immediately observable by human analysts. These capabilities have already led to significant advancements in several fields, including drug discovery, materials engineering, manufacturing optimization and personalized education. Within the case study organization, this process was particularly visible in the analysis of large-scale datasets aimed at identifying emerging cybersecurity threats. As one participant observed, “GenAI helps re-elaborate explicit knowledge and transform it into a potential source of innovation and improvement, even starting from previously produced synthetic data.” Despite these capabilities, human actors remain essential in evaluating and validating AI-generated insights. The interpretation and critical assessment of newly generated knowledge are necessary to ensure its reliability and practical relevance. In this sense, humans play a key role in integrating AI-generated outputs into organizational knowledge processes. Ultimately, this conversion dynamic represents the culmination of the AI-mediated knowledge creation cycle, generating new forms of artificial knowledge that may trigger further iterations of learning, refinement and innovation.

5.1 Managerial Implications

From a managerial perspective, the framework suggests that GenAI should be embedded into knowledge management processes through clearly defined use cases, such as data synthesis, documentation support and exploratory analysis, rather than being adopted in unsanctioned manner. Managers are encouraged to formalize human-in-the-loop validation practices, assigning explicit responsibility for reviewing, interpreting and approving GenAI outputs in critical decision processes. Furthermore, continuous training initiatives and shared guidelines on responsible GenAI use are essential to prevent over-reliance on automation while sustaining employees' critical thinking and learning capabilities.

5.2 Limitations and Future Research

Like any research, this study presents several limitations that should be acknowledged. First, the findings are derived from a single case study. Although the selected company represents a particularly suitable context for investigating the integration of GenAI into knowledge-intensive workflows, the results cannot be generalized without caution. Future research could address this limitation by adopting a multiple-case study design, allowing the proposed framework to be tested and refined across organizations with different levels of technological maturity, innovation orientation and organizational complexity. A second limitation concerns the sectoral scope of the study. The empirical investigation focuses on a single industry context, namely the IT sector, which is characterized by high technological intensity and strong familiarity with digital tools. As a result, the dynamics observed in this environment may differ from those found in other industries where the adoption of GenAI is less mature. Extending the analysis to organizations operating in different sectors could provide valuable insights into the broader applicability of the proposed framework. As with most qualitative research, the findings may also be subject to potential observer and participant biases. To mitigate these risks, the study relied on established qualitative research methods and rigorous procedures for data collection and analysis, including systematic coding, iterative validation of categories and triangulation through multiple data sources. Finally, while the study proposes an integrated conceptual framework for understanding the interaction between human and machine dimensions in knowledge creation, further research is required to clarify its boundary conditions and applicability. In particular, future studies could examine how the framework performs across different organizational contexts, levels of GenAI adoption and knowledge management practices.

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Ethical Declaration: All participants were informed about the nature of the study and participated voluntarily. Clearance was not required for the research.

AI Declaration: Generative AI tools were not used in the production or analysis of the empirical data. All interpretations and findings are the result of the authors' critical analysis and are not generated by AI.

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