

# Framing SECI model through an artificial knowledge generation perspective: a case study analysis in the GenAI era

Giuseppe Liccardo , Roberto Cerchione  and Marco Trabucco Aurilio

## Abstract

**Purpose** – This study aims to examine the influence of generative artificial intelligence (GenAI) on the phases of knowledge creation as delineated by Nonaka's SECI model. Furthermore, it delineates the fundamental interactions among the components of a theoretical framework for the artificial knowledge generation through a continuous interaction between human and artificial dimensions.

**Design/methodology/approach** – The authors used an exploratory single-case study to reach their aim. Data were primarily collected through semi-structured interviews and triangulated via direct observation and document analysis within a company operating in the cybersecurity sector. An inductive coding tree was derived from qualitative data analysis performed by using content analysis methodologies.

**Findings** – Data indicates that GenAI significantly influences the SECI phases of knowledge creation. In addition, the influence of this disruptive technology on knowledge generation cannot be adequately described by relying exclusively on the original SECI model, highlighting the need for its extension in the context of artificial knowledge generation.

**Research limitations/implications** – The study identifies developing AI-driven mechanisms that appear to introduce novel knowledge conversion dynamics absent from the original model. These findings resulted in the definition of a novel framework that offers a more thorough comprehension of human-machine collaboration in knowledge management.

**Originality/value** – The originality of this study lies in the systematic analysis of GenAI's influence on the SECI model and the subsequent development of a novel preliminary and empirically informed theoretical framework that extends the SECI model by incorporating a machine dimension into knowledge generation processes.

**Keywords** Artificial intelligence (AI), Artificial knowledge management (AKM), Artificial knowledge generation, SECI, Generative artificial intelligence (GenAI), Learning organizations

**Paper type** Research paper

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## 1. Introduction

Generative artificial intelligence (GenAI) is defined as a subset of artificial intelligence technologies, which can autonomously generate text, images, videos (S. Singh *et al.*, 2024a), audio and code (Bilgram and Laarmann, 2023; K. Singh *et al.*, 2024b) based on previously learned data patterns (Goodfellow *et al.*, 2014). This disruptive technology, due to its potential to improve human efficiency and effectiveness, has garnered interest from both public and private organizations (Felicetti *et al.*, 2024). Consequently, many companies are heavily investing in this tool (Lee *et al.*, 2023). Current literature suggests that GenAI adoption will introduce radical changes on people and organizations in the future years. Notably, this shift will involve even those organizations that still are not willing to officially integrate GenAI in their practice. The unsanctioned use of such technology among employees, referred to as “shadow AI” (Chin *et al.*, 2025), is expected to influence

organizational processes regardless of official policies. A key challenge for organizational management will be to understand how GenAI transforms corporate operations and decision-making processes. In this context, knowledge management (KM), which encompasses the collection, sharing and creation of knowledge within organizations (Beesley and Cooper, 2008; Gold *et al.*, 2001), plays a crucial role in driving this change (Centobelli *et al.*, 2018; Marques Júnior *et al.*, 2020; Centobelli *et al.*, 2025). Organizations rely on KM to properly use their informational resources and improve both their operational efficiency and creativity (Darroch, 2005). Many foundation models, including the absorptive capacity model (Cohen and Levinthal, 2026), organizational learning model (Crossan *et al.*, 1999) and Nonaka's SECI model (Nonaka, 1994), have successfully described organizational knowledge processes. These models enabled organizations to effectively shape their process for making the best use of knowledge. Regarding the impact of GenAI on KM, recent studies have started to interrogate the adequacy of the foundation models (Böhm and Durst, 2026; Zhang *et al.*, 2025), explored AI-based applications in organizational settings (Leoni *et al.*, 2024) and attempted to develop frameworks to explain human-machine collaboration (Duan *et al.*, 2019; Kim, 2024). Although these contributions provide valuable theoretical insights, a notable gap remains in formalizing how GenAI contributes to knowledge generation. This gap mainly stems from the absence of a comprehensive model that fully accounts for GenAI transformative impact on knowledge creation. With this premise, while a previous study (Cerchione *et al.*, 2026) established the foundational elements of a framework for artificial knowledge generation, the aim of this paper is to empirically investigate the interaction between human and machine dimensions to:

- investigate the impact of GenAI on SECI model; and
- set the foundations to extend the existing SECI model, by seeking to develop an integrated framework that acknowledges the dual dimension of knowledge generation.

This specific KM model has been chosen as conceptual foundation of the study as it explicitly describes the dynamic interaction between tacit and explicit knowledge for knowledge creation, an interaction profoundly impacted by GenAI. This makes the SECI model a particularly suitable lens through which to analyze GenAI impact on organizational knowledge creation processes. To achieve its aim, this study investigates the impact of GenAI on knowledge generation within organizations, a subject of increasing importance in KM research. This research provides theoretical and practical insights by proposing a novel framework grounded on empirical data from an exploratory single case study. The objective is to provoke meaningful discussion on the function of GenAI in KM and to provide a systematic basis for further research in this field. The remainder of the paper is structured as follows. Section 2 reviews the theoretical background and underlines key KM models relevant for this study. Section 3 outlines the research methodology and describes materials of the case study. Section 4 presents the results, while Section 5 critically discusses the empirical findings and concludes the study by outlining implications and future avenues of research.

## 2. Theoretical background

### 2.1 Knowledge management models

The exploration of the concept of knowledge has been rich and varied across the literature. For practical purpose, this section focuses on recent research within the field of KM. Scholars have described knowledge as a multifaceted entity that simultaneously exists as a state of mind, an object, a process, a condition for accessing information and a capability for interpreting data (Alavi and Leidner, 2001). It can manifest in practical, usable forms, recognized by either human or computational processes (Newell, 1982) and can be

embedded within various organizational activities and entities. Polanyi (1958) first introduced the classification of knowledge into tacit and explicit.

Tacit knowledge comprises deeply held beliefs and values, which can only be transferred through direct interaction and continuous engagement with the knowledge bearer. By contrast, explicit knowledge is codified and easily transferable without the direct involvement of originator. According to Dalkir (2011), knowledge is a valuable asset found in people tacit insights, characterized by its non-depleting nature. From a practical standpoint, knowledge represents the ability to apply relevant information purposefully (Lin and Ha, 2015). Regarding on how knowledge is created, Nonaka (1994) introduced the SECI model, which describes how the dynamic transition between tacit and explicit knowledge through various phases continuously generate new knowledge (Nonaka, 1998). Other scholars, such as Crossan *et al.* (1999), have suggested that knowledge creation is an internal organizational process that leverages existing knowledge across individual, group and organizational levels. A complementary perspective is offered by Cohen and Levinthal (2026), who developed the concept of absorptive capacity, which refers to organization's ability to recognize, assimilate and apply new knowledge to gain a competitive advantage. This concept was later expanded by Zahra and George (2002), who differentiated between potential and realized absorptive capacities, highlighting them as critical organizational routines that facilitate knowledge transformation and utilization.

**2.1.1 SECI model.** The SECI model describes the dynamic process of knowledge creation within organizations. According to this model, knowledge conversion occurs through four distinct phases (Figure 1): socialization, externalization, combination and internalization (Nonaka, 1994).

Each phase plays a specific role in transforming knowledge and contribute to creation of knowledge withing organizations (Nonaka *et al.*, 2006):

- *Socialization (tacit to tacit):* This phase involves the creation of tacit knowledge through direct interaction among people, which provide the context for sharing personal experiences.
- *Externalization (tacit to explicit):* The externalization phase focuses on structuring personal tacit knowledge into explicit concepts accessible to others. This process is facilitated through dialogues, reflections, metaphors and analogies.
- *Combination (explicit to explicit):* The combination phase includes the integration and synthesis of various explicit knowledge sources to create more comprehensive knowledge sets. A common example of this process is the production of reports and documentation.

**Figure 1** SECI model phases



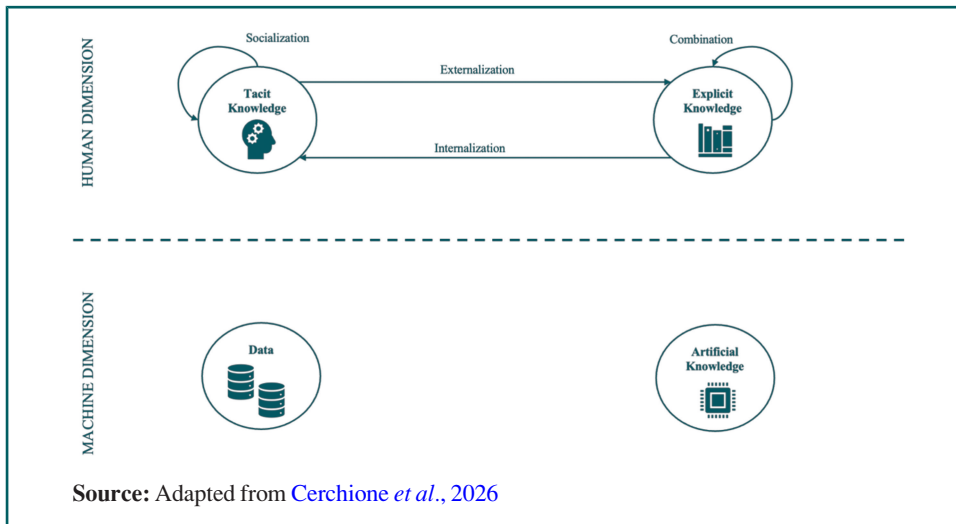
- *Internalization (explicit to tacit)*: Internalization occurs when explicit knowledge is transformed into tacit knowledge. This phase is facilitated by learning by doing, observation, active engagement which allow individuals to internalize insights gained during the other phases.

The SECI model is a well-established framework for understanding knowledge creation through the dynamic interaction between tacit and explicit knowledge. Unlike other KM models, such as the absorptive capacity model, which focuses on the ability of organizations to acquire and use external knowledge, or the organizational learning model, which emphasizes learning across different organizational levels, the SECI model uniquely captures the continuous transformation of knowledge between tacit and explicit forms. Given that GenAI fundamentally influences how knowledge is externalized, combined and internalized, the SECI model serves as the most suitable theoretical foundation for analyzing how human–AI collaboration reshapes knowledge generation processes.

## 2.2 Literature review

An examination of the existing literature on the application of GenAI in organizations reveals its transformative potential from a KM perspective. Organizations across various sectors are trying to integrate GenAI into their processes to augment organizational knowledge bases, improve operations efficiency and foster innovation (Marshall *et al.*, 2024). Through automated content creation, GenAI tools help employees and managers in producing business reports and marketing materials with a high degree of efficiency and even a significant level of personalization (Tafesse and Wien, 2024). This is particularly impactful in software industry, in which GenAI is literally revolutionizing code production and bug detection, resulting in a significant reduction in development time (Gupta *et al.*, 2023). In addition, GenAI has become a powerful tool for predictive analysis, helping in market trend forecasting as its support allows managers to make data-driven strategic decisions (Menéndez Medina and Heredia Álvaro, 2024). In the healthcare sector, GenAI is increasingly used for the generation of synthetic data and advanced analytics, supporting clinical research and personalized medicine while addressing data scarcity and privacy constraints (Wang and Zhang, 2024). This is particularly true in cybersecurity, where firms employ GenAI to support professionals in analyzing network traffic with the aim of detecting anomalies and in developing proactive digital defenses (Schreiber and Schreiber, 2024). In public sector, GenAI is used to enhance digital governance and provide citizens with better services through data-driven insights (Mellouli *et al.*, 2024). Similarly, customer service has been significantly impacted by chatbots, which offer the possibility to implement real-time support and reduce workload for human employees (Leong *et al.*, 2024). Overall, GenAI plays an essential role in setting an innovation-driven environment within organizations. Despite the numerous advantages, GenAI adoption also presents several challenges. Many concerns rise regarding ethical considerations, hallucinations and workforce displacement (Fraile *et al.*, 2023). In this context, continuous human oversight and algorithmic transparency may represent the key factors to mitigate the AI excessive reliance trend (Gupta *et al.*, 2023). To address these concerns, businesses are increasingly investing in responsible AI practices, including explainable AI (XAI) frameworks and strict governance protocols to ensure ethical implementation.

*2.2.1 The dual dimension of knowledge generation.* Upon examining the existing literature regarding the application of GenAI in organizations, it clearly emerges that GenAI holds transformative potential for the acquisition, dissemination and generation of knowledge (A Mooradian, 2024). Nevertheless, a deeper examination of the literature suggests that GenAI's function as a mere auxiliary tool in executing the conventional KM processes is overly simplistic (Zhang *et al.*, 2025). GenAI does not merely enhance existing knowledge (Seeber *et al.*, 2020); rather, it introduces a completely new dimension in knowledge generation (Figure 2). Scientific literature suggests that two distinct dimensions of

**Figure 2** Human and machine dimension

Source: Adapted from [Cerchione et al., 2026](#)

knowledge coexist and interact to generate new knowledge ([Cerchione et al., 2026](#)). The human dimension, defined by conventional methods of knowledge creation, has been thoroughly examined by Nonaka ([Nonaka, 1994, 1998; Nonaka et al., 2006; Nonaka and Takeuchi, 1995](#)). The machine dimension facilitates new forms of human-machine and machine-machine interactions, resulting in innovative knowledge generation. In contrast to the human-centric process outlined by Nonaka, there exists no structured framework for comprehending the generation of knowledge within the machine domain.

This focus on the generative dynamics of the machine dimension distinguishes the present study from recent attempts to revise the SECI model in the GenAI era. [Dai et al. \(2026\)](#) introduce the notion of “dark knowledge” as an additional dimension interacting with the four conversion phases. [Böhm and Durst \(2026\)](#) instead divide each phase into human- and machine-driven roles, foregrounding the novel interaction patterns enabled by GenAI, whereas [Zhang et al. \(2025\)](#) reframe the model around the notion of human-intelligence symbiosis. Although these contributions advance the debate, they tend to foreground the opacity of machine outputs or the redistribution of roles within the existing phases rather than the generative mechanisms of the machine dimension itself.

Drawing upon these premises, this study tries, through an exploratory case study, first to analyze the impact of GenAI on the SECI model phases and then to extend it by uncovering the fundamental relationship occurring between the main elements of human and machine dimensions, a notion that Nonaka attempted to elucidate ([Nonaka and Toyama, 2003](#)) although has remained ambiguous since the emergence of GenAI.

**2.2.2 Data.** The primary component of machine dimension is data. The capacity of GenAI to independently produce new content is fundamentally dependent on the extensive data it analyzes and learns from [Mikalef and Gupta \(2021\)](#). Tacit knowledge is characterized as personal belief, dedication and engagement within a specific context, along with the future vision of individuals, which is challenging to convey without a close personal relationship with the holder ([Bateson, 1979; Nonaka, 1994; Polanyi, 1966](#)). The literature presents two distinct viewpoints about the potential existence of artificial tacit knowledge. The initial perspective regards tacit knowledge as solely associated with human behaviors, judgments and beliefs, rendering it unattainable for machines ([Johannessen et al., 2001](#)). The latter adopts a more inclusive perspective, positing that tacit knowledge occurs in varying degrees. The subordinate levels may be digitally depicted, yielding a form of machine-based tacit knowledge ([Chennamaneni and Teng, 2011](#)). Literature suggests that

reality aligns more closely with the initial approach, wherein data may be seen as a form of implicit knowledge for machines. Data is defined as symbols representing the properties of objects (Rowley, 2007), factual recordings or measurements used as a foundation for reasoning and calculations. Given that deep learning algorithms use data to both generate content and reconstruct its context (Chen *et al.*, 2023), it is essential to explore whether the emergence of GenAI as a disruptive technology necessitates a deeper examination of the potential for perceiving data as a form of tacit knowledge for machines. The quality and quantity of data directly affect the performance of GenAI models, rendering data management and governance crucial for optimizing GenAI potential, analogous to how the quality of human experiences impacts human tacit knowledge (Nonaka, 1994).

*2.2.3 Artificial knowledge.* From a cognitive perspective, humans construct and manipulate analogies based on mental models, namely, structured representations of reality that shape reasoning and decision-making (Johnson-Laird, 1995). Extending this perspective to machines, it can be argued that GenAI systems process data through algorithms to generate novel outputs. In this sense, a machine “mental models” can be interpreted as structured systems of data and computations, as exemplified by foundation models and deep learning frameworks. Accordingly, the machine dimension has evolved beyond its traditional role as a mere data repository, actively engaging in data processing, pattern recognition and decision-making (Vanitha *et al.*, 2020).

Building on this premise, this evolution raises the question of whether artificial knowledge can be defined as distinct from traditional human knowledge. To further clarify this issue, it is essential to distinguish between the functional and epistemological dimensions of knowledge generated by GenAI. From a functional perspective, GenAI systems are capable of producing outputs that closely resemble human-generated knowledge artifacts, as they can recombine existing information to generate novel content. In this sense, such outputs can be considered functionally equivalent to human knowledge, as they fulfil similar practical purposes (Jashapara, 2004; Turban *et al.*, 2005). This view aligns with the notion of “actionable knowledge,” whereby information is processed and applied to address specific problems.

However, from an epistemological standpoint, the extent to which these outputs can be considered “knowledge” in the human sense remains open to debate. Human knowledge is deeply rooted in experience, intentionality and contextual understanding (Johannessen *et al.*, 2001), whereas GenAI relies on statistical patterns derived from data (Chen *et al.*, 2023). Therefore, while GenAI can replicate the outcomes of knowledge processes, it does not necessarily reproduce the underlying cognitive and interpretative mechanisms. This raises a broader question regarding whether machines can develop not only actionable but also conceptual knowledge, understood as the ability to interpret and assign meaning to information in a way comparable to human expertise (Pearlson *et al.*, 2020).

This issue is further complicated by the increasing codification of digital knowledge enabled by contemporary technologies (Cerchione *et al.*, 2024). While such technologies allow for the structuring and storage of knowledge in digital form, the boundary between data and what could be considered as new form of knowledge remains blurred (Fakhar Manesh *et al.*, 2021; Lin and Ha, 2015). Consequently, conceptualizing artificial knowledge remains a challenging task, particularly given that knowledge itself is an inherently ambiguous and multifaceted construct (Matayong and Kamil Mahmood, 2013). A foundational step in this process involves recognizing that information generated by GenAI is inherently different from human-produced knowledge (Kim, 2024).

Building on this distinction, in this study we conceptualize artificial knowledge as the result of two complementary processes:

1. knowledge co-created through human–AI interaction; and
2. AI-mediated transformation and recombination of existing knowledge.

From this perspective, machines appear to possess knowledge, albeit in an alternative form, where data and algorithms substitute for human experience and intuition. Crucially, while machines can effectively process and apply information in ways that are functionally analogous to human actionable knowledge, their ability to engage in genuine conceptual reasoning remains an open question that lies beyond the scope of the present study.

### 3. Methods and materials

This study has been designed as exploratory single case study (Xia *et al.*, 2025; Yin, 2014). Specifically, it examines the impact of including GenAI tools in workflow process performed by a small digital enterprise framed within knowledge creation process as described by Nonaka SECI model (Bryman and Bell, 2011). Data were collected from in-depth interviews with the employees of the company (Stake, 1995). The interviews have been conducted individually using computer assisted methods and were semi-structured in the form, which is one of the most common approaches to interviewing in qualitative research (Bryman and Burgess, 1999; Iftikhar and Ahola, 2022). Participants held key roles in R&D and operations departments of the case company. A total of 15 among managers and employees took part in the interviews and their work experience ranged from 2 to 25 years.

#### 3.1 Case selection strategy

Case company was selected according to three factors that are proven to influence the use of a new technology in an existing business environment, namely:

1. company orientation to innovation;
2. company previous technological culture; and
3. organizational complexity.

The use of these three dimensions in assessing the possibility to accept a new technology is strongly supported by many well-established theories. Specifically, the diffusion of innovation theory (DOI) (Rogers, 1962) clearly indicates the innovativeness and compatibility, seen as the degree of alignment between new tech and already used tech, of an organization as a strong driver to new ideas and technology acceptance while organizational complexity as a barrier to new technologies adoption. On the same topic, resource-based view (RBV) of the firm (Wernerfelt, 1983) proposes as enabling factors the level of technical expertise and infrastructure together with the organization dynamic capabilities, while posing organizational complexity as potential risk in reducing firm's ability to focus on adopting new technologies. Finally, Tornatzky *et al.* (1990) with their technology–organization–environment framework (TOE) identifies the existing technology use to positively contributes to new technology adoption in contrast with the organizational size, which could act as barrier (Tornatzky *et al.*, 1990).

**3.1.1 Case company.** The subject of this study is a single organization (Born, 2004; Pettigrew, 1985). Specifically, the observed company is a small enterprise founded in 2013. Its mission is to research, develop and deploy cybersecurity systems, with a specific focus on innovative technologies. Among its customers there are many public and private organizations, and it offers a range of services from cybersecurity solutions to customized software development. What distinguishes this company from its direct competitors is the heterogeneity of its employees' background. This strength has contributed to company success in various innovation projects. In addition to computer science engineers, the company employs professionals from diverse fields, including physicists and mathematicians, helping company in tackling data security problems from a diverse perspective. However, while its heterogeneity constitutes a strength, it also presents potential challenges due to knowledge asymmetries among team members. This company

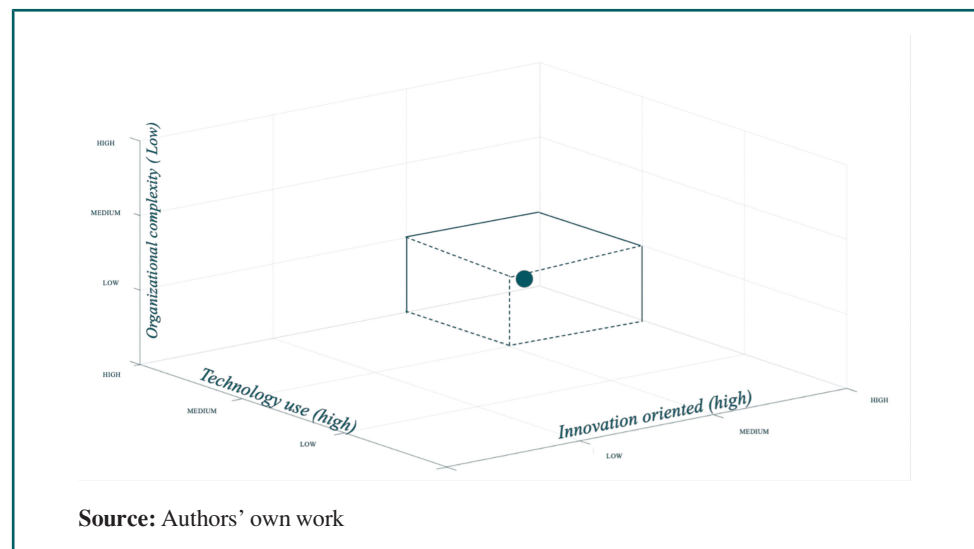
was selected based on its positioning in relation to three key factors that influence the integration of new technologies into organizational processes. Specifically, the company exhibits a high degree of innovation, as evidenced by its extensive history of R&D projects, a strong expertise in the use of technologies and a low organizational complexity as visualized in Figure 3. This combination makes the company an ideal candidate for the present study aim.

### 3.2 Data collection

Multiple sources of information were used to gather data for the present case study (Wilhelm *et al.*, 2013). First, company documentation on three innovation projects was deeply analyzed. This allows researchers to understand the degree of innovation openness and technological use. Second, a kick-off meeting was arranged to illustrate the company structure and working organization, followed by other strategical meetings during the study. This process helped the authors in formulating a protocol of interview that reflected the KM model used as basis while keeping it comprehensible for the interviewees. However, even if other secondary data sources, such as website and project documentation, were used to triangulate qualitative data collected, computer assisted semi-structured interviews were the primary source of information together with field notes produced during the direct observation period which lasted one year and five months (Schou, 2025). The authors, before starting with participants, conducted two pilot tests with senior developers of well-established companies in the software production sector, which have not been included in the analysis. While these pilot test confirmed the clarity of the questions constituting the interview protocol, they helped in some minor revision on the structure of the questions. Thirty interviews were conducted in different phases during the observation period and lasted between 53 and 138 min, with an average duration of 72 min. The participants represented key roles within the R&D and operations departments and senior management board, encompassing a range of professional experiences from junior developers to senior managers.

The content of the interviews was audiotaped and transcribed to ensure a detailed data collection. During the interview particular attention was posed on the neutrality of the interviewers, while at the end, there was space for further informal conversation, which also

**Figure 3** Case study company positioning according to selecting criteria



contained relevant data included in the data collection process. Subsequently, content analysis has been used to analyze the transcription.

*3.2.1 Protocol development.* The protocol of the interview was specifically designed to extract relevant information in relation to the aim of the study. Specifically, the participants were asked to answer questions regarding how they perceive the impact of GenAI on the KM processes and organizational processes. In this context, KM processes refer to all practical operations that contribute to knowledge creation phases as outlined in Nonaka's SECI model. To align with this objective, the protocol was structured into two different sections. The first section included questions aimed to capture the impact of GenAI on the traditional knowledge conversion phases. On the other hand, the second section deals with a deeper level of comprehension of the transformation introduced by this technology. Questions were designed to assess how the organization manage the integration of GenAI within its knowledge processes. Finally, some questions were introduced as conclusion to trigger further discussion regarding the topic.

### 3.3 Data analysis

The data collected were analyzed using content analysis methodology, which allows for the examination of complex phenomena through a formally defined coding procedure (Glaser and Strauss, 1967). The empirical data were categorized through textual analysis and systematically stored using specialized software. Subsequently, an inductive coding tree was developed, incorporating both *in vivo* codes, capturing the exact language used by participants to describe the process under investigation and researcher-generated descriptive codes derived from analytical interpretations (Glaser and Strauss, 1967). By following an iterative approach, the initial codes were continuously refined and adjusted through repeated reviews of the interview transcripts. Then, the codes were systematically compared and contrasted to categorize them into groups of primary themes. After, themes were further organized into a collection of second-order themes, enabling a greater level of abstraction in data analysis Clark *et al.*, (2010). Ultimately, in the final phase, the second-order themes were consolidated into overarching dimensions (Saldaña, 2016). The coding process was further supported by peer debriefing within the research team. Different levels of coding were iteratively discussed and collectively refined, and any divergent interpretations were resolved through discussion until consensus was reached. Dependability and confirmability were reinforced by keeping each stage of the coding process traceable: codes, themes and aggregate dimensions were consistently documented throughout the analysis Clark *et al.*, (2010).

### 3.4 Trustworthiness

As most relevant research on case studies analysis indicates (Eisenhardt, 1989; Yin, 2014), the trustworthiness of the qualitative analysis can be enhanced by incorporating multiple sources of information. For this reason, several secondary documents were analyzed to complement the data obtained via interviews. These included participation in strategic meetings, internet pages, project documentation, database used, prolonged direct observation and scientific articles used to support innovation projects (Gamo-Sanchez and Cegarra-Navarro, 2015). Collectively, these sources contributed to data triangulation. The process used to triangulate data was comparative. The authors cross-referenced the secondary sources mentioned by interviewees with the information contained in the document to validate responses of participants. For instance, when some participants stated that they regularly attended sessions organized to train team members on the use of GenAI tools for data analysis in the early stages of innovation projects, project documentation was analyzed to verify any reference to such meetings and validate their claims. Interviews were conducted in successive phases throughout the observation

period, and data collection continued until theoretical saturation, signifying until no new themes or codes emerged from the participants.

## 4. Results

An inductive coding tree, which represents the core concepts and their relations, was developed from the analysis of the interviews. Specifically, second-order themes and aggregate concepts concerning the impact of GenAI on the SECI model mainly derives from questions in the first section of the protocol, while those related to the broader relationships between the elements of the framework were predominantly derived from the second section of the protocol. However, due to the semi-structured nature of the interviews, it is not possible to precisely map themes on specific questions. They emerged throughout various responses and were often explored in open discussions prompted by multiple questions. Figure 4 shows the first part of the inductive coding tree developed.

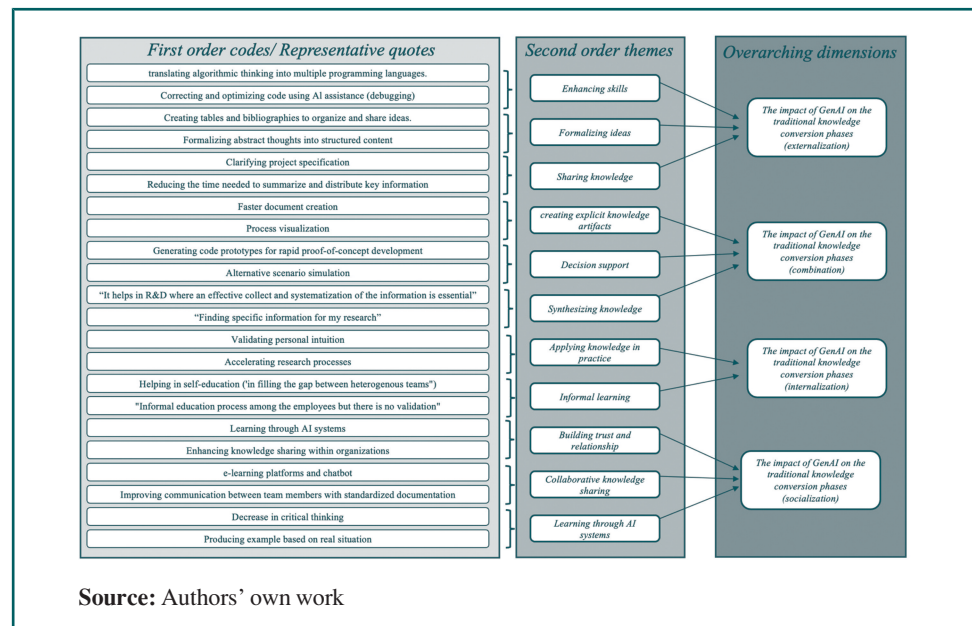
In addition, content analysis revealed that while several themes aligned with the established phases of the SECI model, a significant number of emergent themes could not be directly mapped onto these traditional knowledge conversion processes. Instead, these themes seem to characterize interactions between human-driven knowledge processes and the newly introduced elements of the machine dimension (Figure 5). The findings support the idea that GenAI impact on knowledge creation extends beyond the existing SECI framework.

### 4.1 The impact of generative artificial intelligence on SECI phases

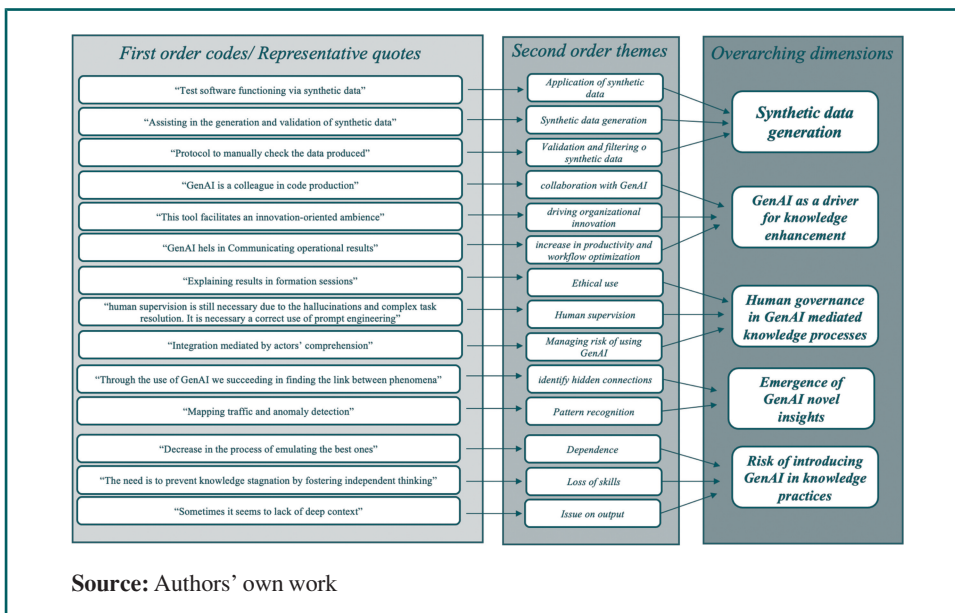
The integration of GenAI within a cybersecurity company presents a profound transformation in knowledge conversion processes. Based on the coding tree analysis, the authors identified its impact on four knowledge conversion phases theorized in SECI model: externalization, combination, internalization and socialization.

**4.1.1 Socialization.** As described in SECI model, the socialization phase emphasizes tacit knowledge sharing through direct and often informal interactions, such as mentorship,

**Figure 4** First part of the inductive coding tree developed, regarding the impact of GenAI on SECI phases



**Figure 5** Second part of the inductive coding tree developed, regarding the interactions between human-driven knowledge processes beyond SECI model



observation and shared experiences (Nonaka, 1994). Within the case company, this phase has traditionally occurred in face-to-face settings, where employees, particularly junior staff, learn from more experienced colleagues through everyday collaboration. The integration of GenAI has partially challenged this process. While some participants highlighted its ability to support collaboration, *"it helps me in transforming my intuitions into more structured content, consequently making them adapt to be shared,"* the overall impact appears to be predominantly negative. This is due to the illusion produced by its inadequate use that interpersonal interaction is no longer necessary. One interviewee clearly stated: *"You can overcome difficulties by your own,"* suggesting a growing trend toward self-reliance through technological mediation. This shift even affects the workplace mentoring culture. With this regard, another participant commented, *"in a work environment where strict timelines must be followed, more experienced colleagues often don't have the time to properly guide you."* This dynamic could be especially detrimental as it undermines the reflective dialogue at the base of critical thinking among employees. As observed by managers, the reduction of traditional mentoring may lead to a decline in analytical skills and conceptual understanding, particularly among the youngest employees.

**4.1.2 Externalization.** The externalization phase traditionally refers to the conversion of tacit knowledge into explicit forms through dialogue, conceptualization and articulation (Nonaka, 1994). In this domain, GenAI appears to be a particularly effective enabler. What primarily emerges from the interview is the use of GenAI as a tool for improving communication among individuals. According to most participants, it enables users to *"give coherence to a stream of thoughts"* and *"find the way to express complex ideas"* through the generation of *"documents that are clear for everyone."* This is especially relevant in highly collaborative environments like R&D and operations. Operationally, GenAI accelerates the creation of explicit knowledge artifacts by supporting the production of *"written reports," "project documentation"* and *"bug detection reports."* It also enables a deeper workflow standardization through *"standardized templates."* Its potential has a twofold impact, while developers use GenAI to enhance productivity in tasks like *"developing code"* or exploring *"different coding languages,"* managers benefit from more efficient document synthesis and subsequent dissemination. GenAI clearly represents a high impact tool to strengthen

the externalization processes within the organization, by simplifying how knowledge is first codified and then shared across roles.

**4.1.3 Internalization.** The internalization phase involves the absorption of explicit knowledge into tacit understanding, often through mechanism such as learning-by-doing and experimentation (Nonaka, 1994). In the context of this phase, GenAI assumes an innovative function of catalyst of individualized learning and context application. Participants reported that GenAI facilitates the acquisition and the subsequent application of knowledge by offering “*customized feedback*,” simulating real-world situations and assisting in translating abstract ideas into practical solutions, or using a senior developer word, “*algorithmic thoughts into code*.” By streamlining access to “*specific information useful for future research from heterogeneous sources*.” Moreover, R&D professionals noted its efficacy in suggesting potential new research directions. Informal learning processes were also boosted by GenAI ability to contribute to recommending “*tailored educational content*” based on individual user profiles, thus enabling a better personalized learning experience. However, the impact of this technology on the internalization process raises some concerns. One R&D manager cautioned that “*human imperfection in expressing thoughts and the relative process to improve them are an important part of human knowledge acquisition process*.” While GenAI aids in structured knowledge acquisition, it may unintentionally obscure the iterative, sometimes confused process of learning that is essential for deep understanding and critical reasoning. Nonetheless, if wisely combined with formal training, GenAI offers the case company a valuable tool to bridge knowledge gaps across case company heterogeneous workforce.

**4.1.4 Combination.** The combination phase refers to the integration of different explicit knowledge artifacts through synthesis and systematization (Nonaka, 1994). Among the SECI model phases of knowledge creation, combination seems to be the most impacted by GenAI advent. Considering the nature of its outputs, which are mainly based on statistical inference and pattern recognition, it is not surprising that this technology excels in aggregating and synthesizing information from various formal sources to produce structured documentation. Its strategic role in facilitating decision-making processes by “*structuring the various processes that have been carried out in a more logical way, along with the relationships between different activities*” is strongly evident from the interviews. It serves not merely as writing tool, but it is also used for workflow optimization and cross-functional coordination. Participants particularly noted the value of GenAI in exploring “*alternative scenarios*” and facilitating problem-solving through its ability to offer structured information based on data. It further enables users to “*add relevant information to core ideas*” and identify “*key sections of documents to review*.” It is particularly true in R&D department, where efficient knowledge integration is critical, as one participant stated: “*It helps in R&D, where an effective collection and systematization of information is essential*.” Considering the application of GenAI with reference to combination within the case company, it significantly boosts the organizational ability to manage complexity. Specifically, it helps in aligning decisions with data-driven insights, and in optimizing knowledge exchange processes. Table 1 summarizes GenAI impact on SECI model phases.

## 4.2 Synthetic data generation

The use of GenAI in cybersecurity presents unique opportunities, particularly through its ability to generate synthetic data. This is an enormous advantage in producing testing environments, as one senior developer noted: “*Generating synthetic data to conduct in-depth analyses on the algorithms that form the core of new services*.” In addition, it supports the creation of training data sets and the refinement of AI-driven security tools. However, synthetic data generation in an organization represents a real advantage only when data validity is ensured, and biases are effectively prevented. The case study company has implemented rigorous validation protocols, which involves multiple phases of human

**Table 1** GenAI impact on SECI model phases

| <i>Socialization</i>                            | <i>Externalization</i>                                       | <i>Interiorization</i>                                      | <i>Combination</i>                        |
|-------------------------------------------------|--------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------|
| ■ Informal education process without validation | ■ Assistance in generating template for formal documentation | ■ Customized feedback                                       | ■ Information synthesis from documents    |
| ■ Decrease in critical thinking                 | ■ Code generation from algorithmic reasoning                 | ■ Scenario simulation                                       | ■ Data extrapolation from databases       |
|                                                 | ■ Standardization of learning process                        | ■ Access to complex information                             | ■ Technical report generation             |
|                                                 |                                                              | ■ Increase in active learning and development of new skills | ■ Information retrieval and visualization |

Source(s): Authors' own work

oversight, “*Careful human supervision to effectively mitigate bias and discrimination,*” as well as privacy filters, “*Data is shared only after all necessary measures have been applied to ensure compliance with privacy regulations.*” Furthermore, organizations must prioritize random sample validation and protocols for autonomous data check to mitigate potential risks associated with synthetic data set generation. As emerged from one interview:

Yes, we definitely have manual supervision. If the data passes this oversight, the generated data is then used as input, or rather, as a prompt, for the next round of data generation. If the final error rate remains below a certain threshold, the data is validated, and the process continues.

Implementing an effective strategy to benefit from the advantages of synthetic data generation is paramount for all organizations, as it allows access to large volumes of specialized data that would otherwise be difficult to obtain.

#### 4.3 Generative artificial intelligence as a driver for knowledge enhancement

The use of GenAI in the case study company confirmed its potential to drive innovation and increase productivity. By stimulating creativity and promoting an innovation-oriented environment, it has become an essential tool for modern organizations. As one participant highlighted, “*In my opinion, the use of these powerful generative tools naturally fosters a work environment that is more innovation-oriented.*” Organization can take advantages from the cooperation between human and GenAI in code production, in aggregating fragmented information and finding the best way to optimize research efforts. As described by one employee:

In the company, software production is the core business, and this technology has become an essential ally, a colleague, especially in code generation. However, its applications go beyond coding and are also used in other business processes, such developing new services designed by the research department.

As described, GenAI supports decision-making process via complex scenario simulation and service optimization. Additionally, GenAI contribution to workflow automation and internal process optimization has led to significant productivity gains, particularly in software development environments. As one senior full-stack developer explained:

From my perspective, this technology will radically transform work processes by enhancing automation, learning and knowledge sharing, provided it is used correctly. Based on my early

experiences with it, this shift is already becoming evident among developers. Conversations within the industry sector indicate that it is reshaping both training and work methodologies for professionals.

Notably, it also provides benefits from a management perspective, assisting in project scheduling and resource allocation, as highlighted by one manager: *"GenAI helps me in scheduling activities."* However, the benefits of this transformation will only be fully realized if organizations actively integrate GenAI into their workflows, rather than passively accept its change. As one senior team member emphasized, *"effectively integrating GenAI in workflow process is the key. The risk is to be passively affected by this revolution."* This has been stressed by multiple managers and senior members of the organization, evidencing the importance of a strategic integration in adopting GenAI.

#### 4.4 Emergence of generative artificial intelligence novel insights

GenAI has demonstrated its capability to identify hidden connections within large data sets, making it highly valuable across various domains that rely on complex data analysis. It enables organizations to uncover relationship that may remain unobserved, *"GenAI allows you to notice some elements that you may overlook."* The case study company applies this potential to detect anomalous patterns, map network traffic and highlight previously unnoticed connections between security threats. As described by a cybersecurity expert interviewed: *"GenAI helps in mapping traffic and anomaly detection. Moreover, it helps in highlighting connection that were not evident and bringing new elements to light."* The responsible integration of this technology into its operations, allows the company to increase the value of its delivered service by strengthening proactive defenses against cyber treats. In addition, the ability to efficiently connect various elements of the internal and external business context *"helps in finding the link between phenomena"* and contribute to the generation of new insights.

#### 4.5 Human governance in generative artificial intelligence-mediated knowledge processes

Case analysis confirm that ethical considerations and human oversight remain critical in GenAI-human integrated workflows. The organization, which is currently trying to systematically adopt this technology into its process, explored multiple approach to address the issue of its ethical use. These range from common sense measures, such as trying to predict output in advance and ensuring an effective comprehension of the generated output, to more articulated approaches, such as periodic conformity audit, *"Strict protocols that include periodic audits for data monitoring and control."* Additional measures involve validation procedures and prompt engineering, *"Good answer mainly depend on good prompts"* and using XAI algorithms. The case study revealed a strong emphasis on critically reviewing all GenAI output, as well as a strong belief that human oversight remains essential for controlling and interpreting them. As technical director explained:

The role (of the users) must be highly critical. It is essential to have a clear expectation of the possible output, and, most importantly, validate it critically rather than assuming it is entirely accurate.

The cybersecurity sector demands rigorous data security and privacy regulations compliance, making it imperative that all GenAI outputs undergo human review. In addition, GenAI models still require improvements as their answers are often too simplistic and may exhibit hallucinations. The risk of misusing GenAI within organizations are serious. However, one critical success factor of new learning company depends on balancing human supervision with GenAI automation to mitigate AI-generated errors. This can be achieved through a series of mitigation strategies such as testing GenAI on synthetic scenarios first,

prompt sharing for improving employees GenAI skills, explaining models functionality and establishing shared best practice, as emerged by the interview:

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.

Ultimately, what is paramount is “*not to see answer as the only truth*” and improve employees’ critical evaluation skills.

#### 4.6 Risk of introducing generative artificial intelligence in knowledge practices

During the study development, while many interviewed were firmly convinced that GenAI would improve working experience and even life, citing various reasons to support their view, an equal number of concerns were raised regarding its negative effect on both its personal use and work-related tasks. Despite its advantages, GenAI presents relevant risks related to “*excessive dependence*” and human capabilities degradation. What managers noticed is that employees may develop excessive dependence on AI-generated content, resulting in the “*loss of capacity to elaborate data from their own*.” This risk is twofold. On the one hand, it is particularly pronounced among less experienced professionals, who “*think to compensate for knowledge gaps*,” potentially bypassing critical learning processes, by relying solely on GenAI support. Additionally, there is a growing concern that the habit of using AI for instant solutions could lead to a “*decrease in the process of emulating the best ones*,” limiting the development of professional expertise over time. On the other hand, highly skilled professionals and managers are not immune. As technology automates increasingly complex cognitive tasks, they fear the possibility of losing their competitive advantages. Moreover, GenAI outputs, when not critically revised, can cause users to “*lose the focus and explore wrong alternatives resulting in losing time*” on unproductive paths. Overall, what emerges from the interviews is a profound change in the traditional process of experiential learning, as professionals, particularly younger ones, may struggle to develop independent analytical skills. In the long term, an overreliance on GenAI for decision-making may erode critical thinking skills and creative problem-solving capabilities. To mitigate these risks, organizations must work on “*actively integrate this tool into operational workflow and employees training programs*,” ensuring that AI serves as an augmentation tool rather than a substitute for critical human expertise (Del Giudice *et al.*, 2023). Another crucial aspect is to establishing clear guidelines for responsible AI use, encouraging workers and managers in using AI systems ensuring a balance between its support and human judgment (Iaia *et al.*, 2024).

Table 2 shows the main benefits and risks emerged for the transcripts.

## 5. Discussion

### 5.1 Organizational dynamics of generative artificial intelligence adoption

Although GenAI is widely regarded as a strategic instrument, it is predominantly considered as a supporting tool rather than an autonomous source of knowledge. Nevertheless, responses to interviews reveal the profound influence this technology has had on the conceptualization of work and information exchange dynamics. It is noticeable that, although the majority of participants agree on GenAI effectiveness in formalizing ideas and facilitating the externalization of thoughts, there exists a clear inclination to retain control over this technology (Arias-Pérez and Vélez-Jaramillo, 2022). A salient point that emerged from the interview is the more prudent stance characterizing managers, in contrast to the openness to the full potential of GenAI showed by employees. This trend can be ascribed to two major elements. First, GenAI use raises concerns around accountability, necessitating a deeper engagement in discerning the true authorship of a completed activity. Second, it introduces a perceived erosion of hierarchical authority, as junior employees may cultivate

**Table 2** GenAI benefits and risk as emerged from data analysis

| Level of analysis | Benefits                                                                                                                                                                                                                                                                                                                                                                                                          | Risks                                                                                                                                                                                                                                                                                                                                                                                                                                                 |
|-------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Organizational    | <ul style="list-style-type: none"> <li>■ Increase in productivity (automation of repetitive tasks, optimization of workflows)</li> <li>■ Improved work quality (support in creating accurate documentation, data analysis)</li> <li>■ Facilitating innovation (exploration of new ideas, development of innovative products and services, maintaining competitiveness in a constantly evolving market)</li> </ul> | <ul style="list-style-type: none"> <li>■ Dependence on technology (reduced internal skills, loss of control over decision-making processes)</li> <li>■ Ethical issues (risk of bias and discrimination, need to ensure data privacy, accountability for decisions based on GenAI outputs)</li> </ul>                                                                                                                                                  |
| Individual        | <ul style="list-style-type: none"> <li>■ Development of new skills (improvement of work performance, increased possibility in self-learning, greater confidence over complex tasks)</li> <li>■ Personalized learning (tailored learning experiences)</li> <li>■ Greater autonomy (quick access to information to solve problems independently)</li> </ul>                                                         | <ul style="list-style-type: none"> <li>■ Reduction in critical thinking (reduced individual abilities to autonomously approach to problems)</li> <li>■ Dependence on technology (decreased in critical thinking and increasing difficulties in developing original solution)</li> <li>■ Ethical issues (individuals must be aware there are the first responsible especially when decision taken by consulting GenAI involve other people)</li> </ul> |

Source(s): Authors' own work

the perception of attaining comparable skills to their more experienced colleagues and supervisors (Wikström *et al.*, 2018). One of the most distinctive characteristics of the case company is its highly heterogeneous workforce. While this diversity constitutes a core organizational strength (Ganguly *et al.*, 2019), it also presents considerable barriers to training individuals across various sectors. This peculiarity adds another layer of complexity in a field, cybersecurity, in which operational capability is closely related with innovation and emerging technologies engagement. In the light of this consideration, the ability to purposefully use internal and external knowledge is essential to maintain operational capability (Du Plessis, 2007). This condition highlights the urgent need for effective strategies to internally disseminate both explicit and tacit knowledge. In this regard, GenAI is perceived as a promising tool for mitigating information asymmetry and enhancing productivity (Botega and Da Silva, 2020; Papa *et al.*, 2020). In practice, GenAI is widely recognized as a powerful instrument, however, its effectiveness fluctuates significantly depending on users' familiarity with the research domain. Many participants express similar concerns over the complete reliance on GenAI for knowledge retrieval. They warned that the risk is to being overwhelmed by data rather than adhering to a coherent research trajectory. These insights not only echo but deepen existing concerns surrounding the use of this disruptive technology (Wei *et al.*, 2025; Zhou *et al.*, 2025; Gupta *et al.*, 2023). Overall, GenAI has begun to transform how individuals think and work. Yet, this transformation seems to be more visible among younger employees. Older professionals appear to embrace its potential, though without significantly altering, or at least not openly admitting it, their conceptual frameworks.

## 5.2 Artificial knowledge generation framework

Drawing on the extant literature, the present study moves beyond merely acknowledging the possible existence of an alternative form of knowledge (Dai *et al.*, 2026; Zhang *et al.*, 2025) or introducing a novel knowledge interaction field (Böhm and Durst, 2026). It

proposes a novel framework (Figure 6) that tries to elucidate how knowledge is co-produced through the interaction between human and machine dimensions within organizations. The framework's structural backbone draws on two elements grounded in prior theoretical and empirical work. First, Nonaka's SECI model was adopted to represent the human dimension of knowledge creation. Second, given the disruptive nature of GenAI, a complementary machine dimension, together with its constituent elements (Cerchione *et al.*, 2026), was incorporated to account for the role of GenAI in the knowledge creation process. These two elements provide the structural scaffolding of the framework.

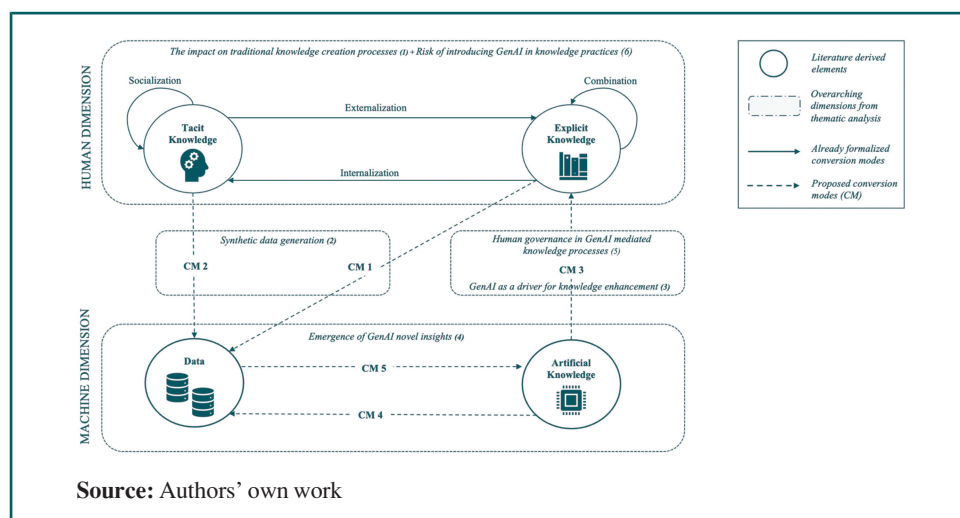
Building on this structure, the overarching dimensions that emerged from the case analysis were mapped onto the framework, each positioned according to its substantive relevance to the surrounding structural elements. Finally, drawing on the patterns identified through the case analysis, a set of conceptual relationships linking the framework's key elements was developed. These relationships, which we term conversion modes (CMs), cut across the thematic areas from which they were empirically grounded, capturing the dominant dynamics through which knowledge is translated and recombined between the human and machine dimensions.

**5.2.1 Conversion modes.** To further unpack the internal logic of the proposed framework, this section elaborates on the underlying dynamics through which knowledge flows and transforms across the human and machine dimensions. A closer examination of the empirical material reveals a set of recurring patterns in how knowledge is translated and recombined. These patterns have been analytically abstracted into a set of CMs, which should be interpreted not as discrete empirical events, but as conceptual mechanisms that capture the dominant knowledge transformation processes observed in the case.

*CM1: from human explicit knowledge to data*

A first recurring pattern observed in the case concerns the translation of human explicit knowledge into machine-readable formats, conceptualized as CM1. This process reflects how human expertise is formalized into structured data sets that can be processed by AI systems. In this sense, the quality of data is not merely a technical issue, but the result of interpretative and filtering activities carried out by human actors, who play a crucial role in preserving contextual richness while enabling machine learning processes. This conversion

**Figure 6** Conceptual framework extending the SECI model through the integration of human and machine dimensions and the associated knowledge conversion modes



mechanism represents a foundational step for establishing a reliable interaction between human and machine dimensions.

#### *CM2: from tacit human knowledge to data*

A second pattern emerging from the analysis relates to the ability of AI systems to learn from the outputs generated by humans, even when these are not explicitly produced for training purposes. This dynamic is conceptualized as CM2. Prior research suggests that tacit knowledge can be partially externalized through digital traces such as text, audio and video (Hildrum, 2009; Panahi *et al.*, 2016). In this context, AI systems continuously analyze large volumes of heterogeneous data, identifying patterns in language, behavior and decision-making processes. However, this mechanism also introduces significant challenges, particularly related to bias propagation and the need for careful algorithmic design and governance.

#### *CM3: from artificial knowledge to human explicit knowledge*

Another key pattern identified in the analysis relates to the reintegration of artificial knowledge into human cognitive processes, conceptualized as CM3. Given the complexity and opacity of deep learning models, this process leads to the importance of interpretability and transparency. In this regard, XAI approaches (Barredo Arrieta *et al.*, 2020) play a crucial role in enabling humans to understand and critically assess these novel outputs. This CM is particularly relevant in high-stakes domains such as healthcare (Reddy, 2024), finance and law (Sachan and Liu, 2024), where trust and accountability are essential.

#### *CM4: from artificial knowledge to data*

A further pattern concerns the increasing autonomy of AI systems in generating new data, conceptualized as CM4. This mode reflects a shift in the AI role from a passive recipient of data to an active contributor in the knowledge creation process. Techniques such as generative adversarial networks (GANs) and variational autoencoders (VAEs) enable the creation of synthetic data sets, which can be used to further train models. While this development opens new opportunities for knowledge generation, it also raises critical issues related to overall control and validation, which, once again, underlines the importance of human involvement in supervising AI outputs.

#### *CM5: from data to artificial knowledge*

Finally, a critical pattern identified is the generation of novel insights by AI systems, conceptualized as CM5. This represents the highest expression of the machine dimension's contribution to knowledge generation, where GenAI systems, generate new insights across multiple domains (Krishnan *et al.*, 2024; Lan *et al.*, 2024). Importantly, human actors still remain essential in interpreting, validating and then integrating this newly generated knowledge. In this process lies the hybrid nature of the new knowledge creation process.

## 6. Conclusion

### 6.1 Theoretical implications

This study offers several contributions to the KM literature. First, it proposes a novel exploratory framework, empirically informed, which serve as foundation for extending traditional SECI knowledge creation model and accounts for machine dimension, thereby moving beyond the human-centric perspective that has historically characterized this field (Cerchione *et al.*, 2026; Dai *et al.*, 2026). Second, it offers a first conceptualization of artificial knowledge, distinguishing between its functional and epistemological dimensions and framing it as a hybrid outcome produced by both the interaction between human and machine and knowledge transformation through the use of GenAI (Kim, 2024). Third, the study proposes a set of CMs as analytical mechanisms that explain how knowledge flows and evolves across human and machine domains (Böhm and Durst, 2026).

## 6.2 Managerial implications

This study provides several practical implications for managers seeking to integrate GenAI into KM processes. First, the findings highlight that, far from being a mere technological issue, the effective use of GenAI requires active human involvement. It is especially true in two distinct moments:

1. in the early stages of data preparation, when human intervention is essential for filtering data; and
2. before the integration of ai-generated outputs into the organizational knowledge base for structuring their evaluation (Zhang *et al.*, 2025).

According with this consideration, organizations should invest in data quality management practices, as the performance and reliability of GenAI systems are highly dependent on the richness of input data and should adopt particular attention to interpretability of the generated outputs (Mikalef and Gupta, 2021). This can be achieved by adopting technical practices such as the use of xAI algorithms and by establishing human validation mechanisms to ensure that artificial knowledge can be, first, effectively understood and then responsibly used in decision-making processes. In addition, the identified CMs suggest that managers need to design hybrid knowledge workflows, where human and AI roles are clearly defined and complementary, rather than assuming full automation (Del Giudice *et al.*, 2023; Iaita *et al.*, 2024), thereby promoting employees' positive response to organizational uncertainty and change and potentially influencing their engagement with, and trust in, newly introduced tools and practices (Zixian *et al.*, 2026).

## 6.3 Limitations and future research

Like any study, this research presents some limitations. First, considering its qualitative nature, the findings of the present work are subject to both observer bias and participant bias. In the case of observer bias, there is a risk of misinterpretation of data or wrong aggregation of concept through inductive reasoning. Participant bias could be caused by misunderstanding or varying levels of awareness of the concept presented in the questions, which could lead to omission of relevant insights. Regarding this first limitation, the author relies on the rigorous application of scientifically validated research methods. Through meticulous control over the data collection and analysis phases, it has been possible to extrapolate finding with scientific rigor and minimizing potential biases.

Second, since the findings are derived from a single case study and the company operates in a sector characterized by high developed digital capabilities, there may be some issue in generalizability. To address this second limitation, the authors position the main contribution of this study as an exploratory framework grounded in empirical evidence without pretending to offer a fully established model. Nevertheless, consistent with the notion of analytical generalization (Yin, 2014), the empirically grounded framework proposed in this study may provide transferable theoretical insights into the relationship between human and machine dimensions in knowledge generation, while its applicability across different organizational and industry contexts requires further empirical investigation. This limitation points toward the setting of a multiple case study, selecting organizations with varying levels of digital maturity and operating in different industries, to better understand the boundary conditions of the proposed framework and assess its applicability across diverse contexts. Finally, while this study adopts an exploratory qualitative approach, future research could complement these findings through quantitative validation, for instance by operationalizing the proposed framework and empirically testing the relationships between its key components.

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