GenAI-Assisted Knowledge Generation: A Case Study on Human-Machine Collaboration Through the SECI Model

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Abstract - This paper analyses the impact of Generative Artificial Intelligence (GenAI) on the traditional phases of knowledge creation theorized Nonaka's SECI model. To the purpose, an exploratory single-case study was conducted using semi-structured interviews, direct observation and document analysis within a company operating in the cybersecurity sector and software development. The case company was selected based on its strong innovation orientation, technological culture, and moderate organizational complexity, which are three factors influencing technology adoption in business environments. Interviews were conducted with employees and managers from the R&D and Operations departments, and data were triangulated with secondary sources. Qualitative data were analysed through content analysis methodology, generating an inductive coding tree. The study reveals that GenAI significantly impacts knowledge creation across existing SECI phases. Specifically, while it supports externalization, combination and internalization by facilitating knowledge transformation processes, its impact on socialization presents both opportunities and risks, particularly in the replacement of human interactions. Moreover, results reveal differentiated effects of GenAI across the SECI phases. GenAI enhances externalization, combination, and internalization by supporting the generation of formal templates, code synthesis, report creation and personalized feedback, while its effect on socialization is more ambiguous, raising concerns about critical thinking and the erosion of informal peer learning. These findings suggest that GenAI holds transformative force within knowledge dynamics, offering a unique opportunity to reconsider how human and machine-generated knowledge co-evolve. The paper's novelty and significance reside not only in the analysis of GenAI impact on well-established KM model but also in its capacity to offer organisations interesting insights on effectively integrating it into their workflows.

Keywords Learning organizations, Artificial knowledge management (AKM), Organizational knowledge, SECI, Generative artificial intelligence (GenAI)

1. Introduction

Academic studies define Generative Artificial Intelligence (GenAI) as a technology capable of autonomously generating new content (Dwivedi et al., 2023), including text, images, videos, and audio (S. Singh et al., 2024). This process is made possible through deep learning (DL) models trained on vast datasets, combined with advanced architectures like transformers and fine-tuning techniques that enable AI to generate contextually relevant outputs (Goodfellow et al., 2014). The disruptive nature of GenAI has drawn increasing attention from both public organizations and private companies due to its potential to enhance human efficiency and effectiveness (Felicetti et al., 2024) . As a result, many organizations are making substantial investments in this technology (Lee et al., 2023). Even those that appear uninterested are indirectly influenced by it through the phenomenon of shadow AI, which describes employees' unsanctioned use of this technology (Chin et al., 2025). The literature clearly indicates that the widespread adoption of GenAI will profoundly transform both individuals and organizations in the coming years. From an organizational management perspective, a key consideration is how this technology will reshape business processes and decision-making structures. Knowledge management (KM), the discipline concerned with the collection, sharing, and creation of knowledge within organizations (Gold et al., 2001), plays a crucial role in this transformation. KM is essential for enabling organizations to effectively leverage their informational resources to enhance operational efficiency and drive innovation performance (Darroch, 2005). Until now, knowledge creation mechanisms within organization have been successfully explained through various models, such as Absorptive Capacity Model (Cohen & Levinthal, 1990), Organizational Learning Model (Crossan et al., 1999) and Nonaka's SECI model (Nonaka, 1994). Among these models, Nonaka's SECI framework is particularly relevant to this study as it explicitly captures the dynamic interplay between tacit and explicit knowledge, a process that aligns with how GenAI facilitates knowledge externalization, synthesis, and internalization. This makes SECI a robust foundation for assessing GenAI's impact on knowledge creation. Nevertheless, while many studies have explored the interaction of AI-based applications in organizational contexts and attempted to explain how this technology foster collaboration (Kim, 2024), a notable gap remains in analysing how GenAI contributes to human knowledge generation, specifically in the highly dynamic context of cybersecurity. In this context, the objective of this paper is to build upon the existing SECI model, aiming to examines the impact of GenAI on knowledge creation within organizations, a topic of growing significance in KM research. By presenting a novel insight based on empirical data collected through an exploratory single case study, this research offers novel theoretical insights. Ultimately, it aims to stimulate meaningful discussions regarding the role of GenAI in KM and provide a structured foundation for future research in this domain. The reminder of the paper is organised as follows. Section 2 presents the theoretical background and foundational KM models. Section 3 outlines the methods and materials used in the case study. Section 4 summarize the findings while section 5 offers a discussion on the empirical results. Finally, Section 6 concludes the paper and highlights potential directions for future research.

2. Theoretical Background

2.1 Knowledge Management Models

Polanyi (1958) was the first to categorize knowledge into tacit and explicit forms. Tacit knowledge consists of ingrained views and values that can only be conveyed by direct interaction and ongoing engagement with the knowledge holder. Conversely, explicit knowledge is documented and readily transferable without the direct participation of the source. Dalkir (2011) asserts that knowledge is a valuable asset inherent in individuals' tacit insights, distinguished by its non-depleting quality. From a pragmatic perspective, knowledge signifies the capacity to actively apply pertinent information(Lin and Ha, 2015) . In this view, it is important to distinguish between what is defined as information and knowledge. Information refers to structured data or facts, while knowledge implies contextualized content that supports action and decision-making. In the context of GenAI, this paper considers its outputs as structured information, which support knowledge creation when interpreted by humans within organizational settings.

Concerning the creation of knowledge, Nonaka (1994) presented the SECI model, which delineates the dynamic transition between tacit and explicit knowledge through four phases that continuously generate new knowledge (Nonaka, 1998). Other academics, such Crossan et al. (1999), propose that knowledge generation is an internal organizational process that utilizes existing knowledge at the individual, group and organizational levels. Cohen & Levinthal (1990) provide a complementary viewpoint by introducing the idea of absorptive capacity, which denotes an organization's capability to identify, assimilate, and utilize new knowledge to achieve a competitive edge.

SECI model

The SECI model is a well-recognized conceptual model that delineates the dynamic process of knowledge generation inside companies via the dynamic interplay between tacit and explicit knowledge. This concept posits that knowledge conversion occurs through four separate phases: Socialization, Externalization, Combination and Internalization (Nonaka, 1994). Each step has a distinct function in the conversion process and contributes to the generation of knowledge inside companies (Nonaka et al., 2006). In contrast to other knowledge management models, such as the Absorptive Capacity Model, which focus on an organization's capacity to acquire and apply external knowledge, and the Organizational Learning Model, which highlights learning across various organizational tiers, the SECI model distinctly encapsulates the ongoing transformation of knowledge between tacit and explicit forms. Considering that GenAI profoundly impacts the externalization, combination, and internalization of knowledge, the SECI model represents the most appropriate theoretical framework for examining how GenAI transforms knowledge generating processes. In this context, it is important to distinguish between information and knowledge.

2.2 Literature Review

An examination of existing literature reveals the transformative potential of GenAI from a Knowledge Management (KM) perspective. Traditional processes of knowledge acquisition, dissemination, and generation are increasingly shaped by this disruptive technology. GenAI contributes to augmenting organizational knowledge bases through the autonomous production of content such as text, images, and scientific insights (Marshall et al., 2024). Across industries, organizations are integrating GenAI to enhance operational efficiency and innovation. In particular, GenAI supports content creation, report writing, and personalization (Islam et al., 2024), while revolutionizing coding and bug detection in software development (Gupta et al., 2023), enabling predictive analytics in decision-making (Menéndez Medina and Heredia Álvaro, 2024) and advancing R&D and product innovation. In cybersecurity, it assists in anomaly detection and proactive defences, while public and customer services benefit from LLMs and chatbots for real-time support and tailored learning (Fraile et al., 2023). Despite its advantages, the literature also highlights ethical concerns, hallucinations, and potential workforce displacement. In this context, human oversight and algorithmic transparency are seen as key enablers of responsible GenAI adoption (Gupta, 2024). Businesses are investing in explainable AI (XAI) and governance protocols to mitigate these risks.

3. Methods and Materials

This study specifically investigates the influence of integrating GenAI technology into the workflow processes of a small cybersecurity firm within the knowledge creation framework outlined by the Nonaka SECI model. Data were obtained through extensive interviews with the company's personnel. The interviews were done individually using computer-assisted methods and were semi-structured, a prevalent methodology in qualitative research (Bryman and Burgess, 1999). Fifteen individuals, comprising managers and staff from the R&D and Operations department, participated in the interviews, with their work experience spanning from two to twenty-five years. The case company was chosen based on (i) the company's inclination towards innovation; (ii) the company's prior technical culture; and (iii) organizational complexity, key factors in technology adoption. The application of these three factors in evaluating the feasibility of adopting a new technology is robustly endorsed by numerous established theories. The diffusion of innovation theory (DOI) (Rogers, 1962) explicitly demonstrates that an organization's innovativeness serve as significant facilitators of the acceptance of new ideas and technologies, whereas organizational complexity acts as an impediment to the adoption of new technologies. The resource-based view (RBV) of the firm (Wernerfelt, 1983) posits that technical expertise and infrastructure, along with dynamic organizational capabilities, are enabling factors, while organizational complexity may pose a risk by diminishing the firm's capacity to adopt new technologies. Finally, Tornatzky et al. (1990) in their technology-organization-environment framework (TOE) assert that current technology use facilitates the adoption of new technology, although organizational scale may serve as an impediment (Tornatzky et al., 1990). The interviews were recorded and transcribed to facilitate comprehensive data gathering. For the whole interview process the authors focus on maintaining a neutral perspective on the topic not to introduce further bias in response collection phase. In the ending part of the interviews, participants had the opportunity for further informal conversation, also included into data gathering procedure. Thereafter, content analysis has been utilized to examine the transcription.

3.1 Data Collection

Computer-assisted semi-structured interviews represent the most relevant source of information of the present work. Before engaging with participants, the authors conducted two pilot tests, not included in the analysis, to confirm the clarity of the questions. The fifteen interviews were conducted in different periods over seven months and lasted between 62 and 120 minutes, with an average duration of 81 minutes. The interview protocol was carefully designed to collect pertinent information aligned with the study's objectives. The initial set of questions was structured to comprehensively address the SECI phases, whilst the subsequent section facilitated a more in-depth exploration of the case company's use of this technology from a general knowledge management perspective. According to prominent research on case study analysis (Eisenhardt, 1989; Yin, 2014), the validity and reliability of interview data can be improved by integrating diverse information sources. Consequently, other secondary materials were examined to augment the data acquired through interviews, including website and project documentation and numerous strategic meetings minutes.

3.2 Data Analysis

The collected data were analysed using content analysis methods, enabling the exploration of complex phenomena through a formally specified coding procedure (Glaser and Strauss, 1967). The empirical data were classified by textual analysis and systematically archived using specialist software. An inductive coding tree was then built, integrating in vivo codes that reflect the participants' precise language and researcher-generated descriptive codes based on analytical interpretations (Glaser & Strauss, 1967). The initial codes were systematically revised and modified through iterative readings of the interview transcripts. Subsequently, topics were systematically categorized in second-order themes, facilitating a heightened degree of abstraction in data analysis (Clark et al., 2010). Ultimately, in the concluding phase, the second-order themes were integrated into overarching dimensions.

3.3 Case

This study focuses on one specific organization (Born, 2004; Pettigrew, 1985). The company in question is a small software house, operating specifically in cybersecurity sector, established in 2013. Its customers include numerous public and private businesses, and it provides a spectrum of services, encompassing cybersecurity solutions and customized software development. The company's distinction from its immediate competitors is in the diversity of its personnel' backgrounds. This strength has facilitated the company's success in numerous innovation initiatives. The company hires experts from a variety of disciplines, such as mathematicians and physicists, in addition to computer science engineers, which enables it to approach data security issues from a variety of different perspectives. While its heterogeneity is a strength, it also poses potential obstacles due to knowledge asymmetries among team members. This company was chosen based on its alignment with three critical characteristics that affect the incorporation of new technology into organizational processes. The corporation demonstrates significant innovation, as indicated by its substantial history of R&D initiatives, robust technological skills, and minimal organizational complexity. This combination makes the company an exemplary candidate for the current study objective.

4. Results

Figure 1 shows inductive coding tree, which represents the core concepts and their relations, developed from the analysis of the interviews. The integration of GenAI within a cybersecurity startup 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.

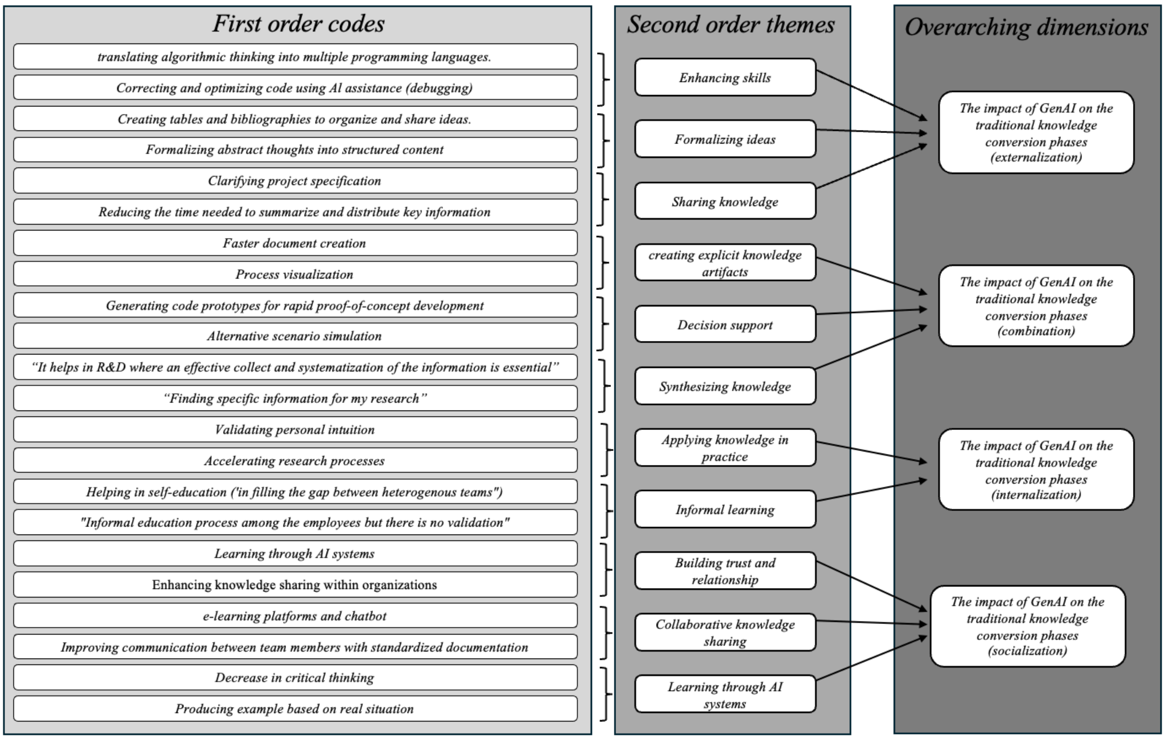

Figure 1*:* Inductive coding tree

4.1 Socialization

The socialisation phase is impacted by GenAI, as it enhances information exchange and collaboration among colleagues in solution development. One participant remarked, "*It assists me in converting my intuitions into more organised content, thereby facilitating their adaptability for sharing*." The overall effect of GenAI on socialisation appears to be primarily detrimental. This is mostly attributed to the misconception of substituting conventional face-to-face conversations with chatbot support. One interviewee remarked, "*You can overcome challenges independently*." Another participant identified a significant issue in the workplace: "*In an environment with stringent deadlines, more seasoned colleagues frequently lack the time to adequately mentor you*." Conversely, they promptly resolve the issue independently, providing you with minimal opportunity to genuinely comprehend or gain insights from the event. The interview with the managers revealed that the gradual replacement of direct socialisation with alternative informal mentorship is resulting in a decline in critical thinking among younger employees. Historically, the capacity for enquiry and reflection was cultivated through in-person contacts, where colleagues engaged in debates that, to some extent, questioned one another's viewpoints. One responder asserted: "*Even in a dynamic environment heavily engaged in innovation, direct experience of the workflow appears to be the most effective method for sharing tacit knowledge*." Nonetheless, technology is regarded as a significant aid in this process, which remains driven by human connections.

4.2 Externalization

The interviews reveal that GenAI is seen as a crucial instrument for converting tacit information into explicit knowledge. This technology assists individuals in organising their thoughts and articulating difficult ideas by producing documents that are broadly comprehensible. From a practical perspective, GenAI assists personnel in efficiently synthesising knowledge into "*written reports*," "*project documentation*," and "*bug detection reports*." A significant benefit is its capacity to standardise workflow procedures via the creation of "*standardised templates*". Developers can utilise GenAI to enhance their efficiency, especially in coding and accessing various programming languages. Simultaneously, managers can leverage GenAI-assisted document synthesis to efficiently generate and disseminate information to staff. In summary, GenAI facilitates information transfer, resulting in a more organised and efficient knowledge-sharing environment within organisations.

4.3 Internalization

The most of participants agree on GenAI's capacity to foster learning application. This is accomplished through the provision of tailored feedback and the simulation of scenarios. Through these interactions, GenAI fosters active learning, allowing users to convert algorithmic concepts into code. Applying information effectively in practical situations is essential for organisations. GenAI enhances the internalisation of new concepts by offering improved access to pertinent information beneficial for future study from diverse sources. Employees are no longer required to focus on whole documents, since GenAI facilitates the extraction of essential insights from them. Furthermore, it assists the R&D department in identifying new research directions to investigate. In addition to enabling organised knowledge acquisition, GenAI contributes to "*organising personal knowledge and enhancing its shareability*." In organisations, informal learning processes are enhanced by GenAI's capacity to recommend pertinent educational trajectories depending on an individual's background, so offering customised learning pathways. Nonetheless, although informal education is frequently beneficial for employees, it lacks formal recognition. The case study company significantly advantages from the systematic incorporation of GenAI into employee training programmes, as it provides the means to address knowledge disparities across its varied workforce. Conversely, as one of the R&D managers observed: "*human fallibility in articulating thoughts and the associated process of enhancement are integral to the human knowledge acquisition process*."

4.4 Combination

Combination is the SECI phase that demonstrates the greatest synergy with this emerging technology. GenAI excels at integrating and synthesising explicit knowledge from diverse formal documents to produce reports, technical documentation, and databases. The case study company recognises the utility of GenAI in facilitating decision-making processes. This technology facilitates the visualisation of intricate workflows by organising the numerous operations in a more logical manner, along with delineating the relationships between distinct tasks. It additionally facilitates the examination of "*alternative scenarios*," enhancing the problem-solving process. Furthermore, GenAI enables experts to interact with extensive datasets by incorporating pertinent information into fundamental concepts and recommending critical areas of documents for examination. One participant remarked, "It aids in research and development, where efficient information collection and organisation are crucial". The potential of GenAI to process and systematise extensive information substantially enhances organisational process optimisation and, once again, offers decision-making help for managers. GenAI enables organisations to enhance knowledge-based decision-making, bolster research and development efforts, and augment efficiency in the creation and distribution of knowledge artefacts.

Figure 2 illustrates the differentiated impact of GenAI across each phase of the SECI model, as emerged from the interview analysis.

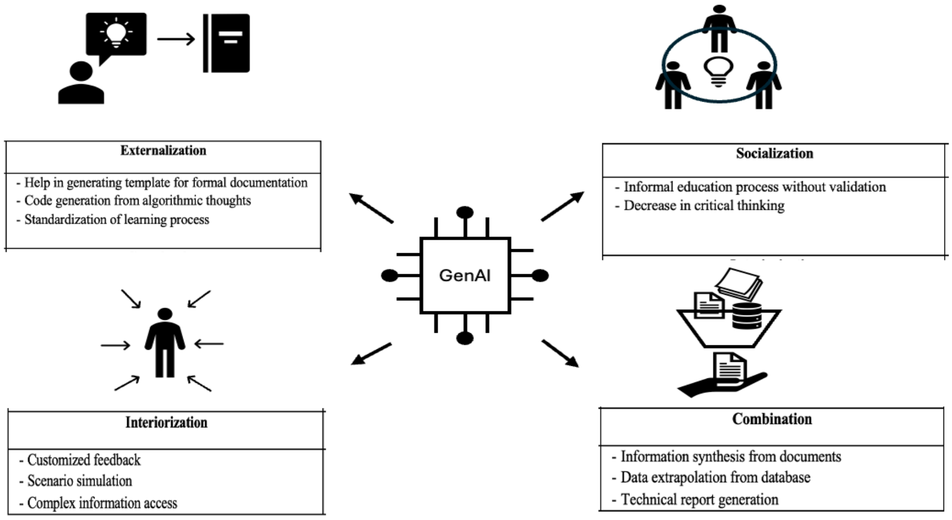

Figure 2*:* The impact of GenAI on SECI model phases

5. Discussion

The company operates in the highly dynamic environment of cybersecurity, where innovation and a strong focus on new technologies are crucial in ensuring operational capability. In this context, the ability to integrate external knowledge and correctly manage internally produced knowledge is a must. The heterogeneity of the workforce presents a significant challenge in training employees who specialize in different sectors. On the other hand, it represents one of the main strengths of the company. This diversity highlights the need for an efficient approach to sharing both explicit and tacit knowledge across the organization. GenAI could represent a potential solution in mitigating information asymmetry and increasing productivity in this complex scenario. As expected, the case study company is actively working to integrate GenAI into their workflow processes and employees' mindset. What emerges from the case study seems to reveal that GenAI rather than just support existing knowledge creation phases activities, it contributes actively in reshaping them. Each phase is impacted differently. Socialization appears to be weakened, as GenAI create the illusion to substitute interpersonal exchanges with chatbot interaction, especially among the youngest. The illusion of self-sufficiency can diminish opportunities for debate and shared reflection, which are essential in developing critical thinking. Interpersonal exchanges, which often involve ambiguity and challenge, represent the setting for critical capabilities development. To Externalize thoughts and intuitions becomes an increasingly automated process, with GenAI supporting the systematization of complex ideas. In practical terms it is done through the production of documentation, code and templates. Combination is the phase which benefits the most from GenAI integration. This novel technology enables the efficient integration of dispersed explicit knowledge into structured outputs, such as technical reports and synthesized analyses. Lastly, internalization requires less time and resource, as users actively absorb new knowledge thanks to adaptive learning pathways and real-world simulations generated by the technology. These findings suggest that GenAI holds transformative force within knowledge dynamics, offering a unique opportunity to reconsider how human and machine-generated knowledge co-evolve. This shift in knowledge creation paradigms underlines the need for a refinement of traditional knowledge management models to better capture the hybrid nature of knowledge creation in this modern context. A noteworthy observation is that, even if most participants agree in GenAI role in formalizing ideas and its ability to allow people externalizing their idea more easily, there is an evident desire to "*maintain power*" over this technology. According to them the risk is to "*leave the right path*" in a sea of fragmented data rather than following a structured research path. Overall, it seems that GenAI has changed the way people work. As one interviewee clearly admitted, "*GenAI will change organizational workflow in a radical way*". However, this transformation seems to be more pronounced among younger employees, while older professionals seem to welcome the great potential of this new tech without necessarily altering (or at least without admitting it) their way of thinking. It remains unclear who is considered the most expose to the phenomenon of losing critical sense due to GenAI dependence. 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 (Wei et al., 2025; Zhou et al., 2025). Table 1 shows the main benefits and risks emerged for the transcripts.

Table 1*: Main benefits and risks emerging from integrating GenAI into knowledge creation processes*

	Benefits	Risks
Individual dimension	Increase in productivity (automation, workflow optimization) Improved work quality (documentation production, data analysis) Facilitating innovation (exploration of new ideas, development of innovative products and services, maintaining competitiveness)	Dependence on technology (reduced internal skills, loss of control over decision-making processes) Ethical issues (bias and discrimination, data privacy, accountability)
Organizational dimension	Development of new skills (work performance, self-learning, complex tasks resolution) Personalized learning (tailored learning experiences) Greater autonomy (access to information)	Reduction in critical thinking (reduced autonomy in problem-solving) Dependence on technology (decreased in critical thinking, difficulties in developing original solution) Ethical issues (responsibility issues for GenAI-assisted decisions)

Concerning the ethical issues summarized in the table 1, they mainly relate to how responsibility is distributed in GenAI-assisted knowledge work. At the individual level, over-reliance may erode foundational human skills. The tendency to defer to GenAI-generated content without questioning its assumptions threatens, not just critical thinking, but also accountability when decisions are based on flawed outputs. At organizational level, ethical issues become more complex and involve accountability of AI-guided decisions which may affect many people. The main concern is that the risk of a systemic shift toward automation in such decisions could marginalize informal mentorship and peer feedback loops, consequently weakening organizational learning culture. These concerns suggest the need for safeguards, such as transparent usage policies, specific ethical awareness for employees and a real integration of GenAI within collaborative rather than isolated workflows.

6. Conclusion

This study aims to examine the influence of GenAI on knowledge generation within organisations, utilising the SECI model as a conceptual framework. By analysing the impacts of GenAI across the SECI phases through an exploratory single case study undertaken on a small enterprise in the highly technological sector of cybersecurity, this study contributes to improving the understanding of human-machine collaboration in knowledge management. The findings underline how each phase is impacted by GenAI, pointing to the need for revisiting and possibly extending the SECI model to better describe this powerful technology transformative impact. The paper's novelty and significance reside not only in an extensive analysis of GenAI impact on well-established KM model but also in its capacity to offer empirical grounding for theorizing an evolved SECI logic fit for AI-augmented organizations.

Limitations and future research

This research, like every study, has several limitations. Initially, as the conclusions originate from a singular case study, even if the chosen organisation is highly representative, there may be concerns regarding generalizability. Regarding this issue, the case study company has been selected as it exemplifies a low-resistance environment for the assimilation of new technology into organisational processes. However, the authors acknowledge that a multiple case study has to be set in order to further validate the results. Secondly, like to all qualitative research, the findings of this study are susceptible to both observer bias and participant bias which poses, on the one hand, a danger of data misinterpretation or erroneous conceptual aggregation via inductive reasoning, and on the other hand differing degrees of comprehension of the concepts outlined in the questions, perhaps resulting in the exclusion of crucial insights. To mitigate this second issue, the authors rely on the rigorous implementation of scientifically verified research methodologies. By exercising strict control over the data collecting and processing processes, it has been feasible to extrapolate findings with scientific rigour while minimising potential biases.

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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