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Driving SME innovation: Generative AI adoption and performance factors

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Abstract

Generative artificial intelligence (GenAI) is fundamentally reshaping the competitiveness of small and medium-sized enterprises (SMEs). This study examines how GenAI affects operational efficiency through automation, human competencies, and organizational transformation. The research methodology is a systematic literature review following the PRISMA 2020 protocol, based on peer-reviewed studies indexed in Web of Science and Scopus. The results highlight that automation alone is insufficient for sustainable competitive advantage; the democratization of technology enhances the value of human skills and strategic thinking. The study concludes that GenAI enables SMEs to innovate and build large-enterprise-level capabilities cost-effectively, provided that adoption is accompanied by the development of organizational culture.

Keywords: generative AI, SMEs, automation, organizational transformation, competitiveness

Introduction

New technologies emerge daily, acting as disruptive innovations that shift previously known paradigms, thereby creating new business challenges and opportunities for SMEs. Global GenAI market forecasts suggest it will reach \$66.89 billion by 2025, growing at an annual rate of 36.9%, and is projected to rise to \$442.07 billion by 2031 (Statista, 2025). AI has become a key technology, as combining customer or process data with AI has created new business models (Von Garrel & Jahn, 2023). The growing prevalence of generative AI is increasingly evident. While traditional AI solutions provide predictions and analyses based on historical data, generative AI is capable of creating new content using its foundation models (Shankar, 2024). Expectations for generative AI are high, best reflected by the fact that the primary focus of more than 275 major technology companies and startups is the further development of generative AI (Murugesan & Cherukuri, 2023). GenAI systems possess three key characteristics: (1) they feature an accessible, user-friendly interface, understand natural language, and generate visual, audiovisual, audio, or text output accordingly; (2) they are capable of creating content that mimics human work; and (3) they are applicable in general use cases (Briggs & Kodnani, 2023).

GenAI has brought several significant changes to organizational life; besides increasing productivity, it has accelerated workforce transformation processes. This is most observable in customer service, research and development (R&D), marketing, and software development, resulting in a need for the workforce to possess

competencies different from those required previously to exploit the opportunities arising from GenAI (Eloundou et al., 2023).

Maintaining competitive advantage is of paramount importance for the SME sector; therefore, it is crucial for them to recognize the benefits that implementing generative AI can bring to the organization (Kemp, 2024). Our research fills a gap in the literature, as an extremely low number of studies address the relationship between SMEs and GenAI. Formulated as a research question, this study asks: How does generative artificial intelligence influence the operational efficiency and competitiveness of small and medium-sized enterprises? The objective of the current research is to map, through a systematic literature review, the changes generative AI implementation brings to organizational life and the areas where it can alter the productivity of small and medium-sized enterprises. More specifically, the study pays particular attention to automation, training, and organizational transformation.

This study contributes to the existing literature by synthesizing fragmented knowledge on GenAI adoption in SMEs, applying a transparent PRISMA 2020-based systematic literature review, and identifying practical implications for SMEs seeking to improve efficiency, innovation, and competitiveness through GenAI. The remainder of the paper is structured as follows: the next section presents the background and literature review, followed by the Materials and Methods section describing the systematic review process. The Findings section summarizes the main results, while the Discussion and Implications section interprets their theoretical and practical relevance. Finally, the Conclusion summarizes the study's contributions, limitations, and future research directions.

Background and Literature Review

Before discussing the productivity-related implications of GenAI, it is important to clarify the conceptual distinction between artificial intelligence (AI) and generative artificial intelligence (GenAI). AI is an umbrella term that includes a broad range of technologies, such as machine learning models, predictive analytics, decision-support systems, and agentic systems. GenAI, by contrast, represents a specific subset of AI that is primarily associated with the generation of new content, knowledge outputs, text, images, code, and other forms of data based on foundation models. Since the present study focuses specifically on GenAI, the term GenAI is used when referring to generative AI-based applications, while AI is used only in broader theoretical or contextual discussions where the cited literature addresses artificial intelligence more generally.

Productivity is a key factor of economic growth, and in this regard, GenAI creates new opportunities for businesses (Filippucci, 2024). Properly implemented GenAI technologies increase company productivity through three main mechanisms: (1) automation of tasks; (2) training and development of employees; and (3) transformation of organizational processes (Calvino et al., 2025).

Automation

New technologies, particularly generative AI, are transforming traditional work models (Pachidi et al., 2021). In the case of automation, human labor is replaced by machines and artificial intelligence, leading to increased productivity and resulting cost efficiency (Acemoglu & Restrepo, 2018). Most studies use microeconomic data as a starting point to measure performance improvement caused by automation, comparing the results of companies using AI with those not using AI. According to research by Briggs and Kodnani (2023), the use of GenAI-supported tools results in an average annual productivity increase of 2.6%, which equates to a 30% growth over a 10-year horizon. Filippucci et al. (2024) conducted a literature review where, comparing the results of several authors, they confirm the findings of Briggs and Kodnani (2023).

The impact of automation can also be measured by processing employee-level data. In this case, the reduction in labor costs can be interpreted as profit, since the use of AI-supported tools reduces the time assigned to individual tasks, thus achieving significant time savings. Acemoglu (2024) assessed the effects of GenAI at the employee level; based on his results, GenAI usage results in a 27% reduction in labor costs over a 10-year interval. Aghion and Bunel (2024), comparing several research results, defined potential savings in ranges, estimating that 27-40% cost efficiency can be achieved among companies using GenAI, thereby supporting Acemoglu's (2024) findings.

Automation entails a decrease in labor demand and wages, which, however, can be counterbalanced by increased demand for non-automated tasks (Przegalinska et al., 2025). Idrisi et al. (2024) highlight that artificial intelligence may cause serious disruptions in the labor market if the development of AI-based technologies exceeds the growth rate of human jobs, which can be mitigated with appropriate government regulation. The number of traditional jobs is gradually decreasing; however, new knowledge-intensive positions are being created linked to the development, auditing, and AI-human collaboration of AI models, requiring retraining and specific sectoral knowledge (Rawashdeh, 2025).

Training

Mayer et al. (2025) highlight in their report that 99% of leaders and 94% of employees have some level of knowledge about GenAI. However, while leaders believe that employees use artificial intelligence for only 4% of their daily working time, in reality, employees utilize the benefits provided by artificial intelligence in at least 30% of their working time on a daily basis.

According to Selenko et al. (2022), the use of GenAI can affect employees in three ways: (1) It changes former methods of task execution, thus forcing employees to transform their previous skills or acquire entirely new ones. (2) The task execution capability of GenAI surpasses human labor, which may lead to job loss from the employee's perspective. (3) New human jobs are created for the development, auditing, and supervision of GenAI, but employees need to possess specific professional knowledge.

In a hybrid work environment built on collaborative activity between artificial intelligence and humans, team dynamics also develop differently (Khoreva & Einola, 2024). In such a work environment, digital tools not only support human work but also influence development and learning processes (Santoni et al., 2024). This new type of workplace learning results in employees having to continuously adapt to new technologies and acquire new skills to cooperate effectively with continuously developing, new iterations of artificial intelligence (Leon, 2023).

Regarding professional knowledge, generative AI can also perform educational tasks. Generative AI is capable of simulating authentic professional problems, producing educational materials, and giving real-time feedback (Callari & Puppione, 2025). Through real-time feedback—realized via automated assessments, performance indicators, and linguistic interactions—it identifies skill areas where the employee has deficiencies, which can then be corrected through targeted interventions (De Laat et al., 2020). GenAI-supported education enables mentoring to be implemented on a larger scale and connects learning activities with workplace performance in various environments (Hakim et al., 2024). At the same time, it is important to emphasize that the quality of educational content generated by GenAI significantly depends on human supervision and, to a lesser extent, on performance goals within the organization (Callari & Puppione, 2025).

Organizational Transformation

Integrating GenAI into organizational life fundamentally changes the organizational dynamics of companies. GenAI alters work practices, induces cultural changes, and reshapes decision-making mechanisms (Murire, 2024). By performing routine tasks, GenAI can optimize organizational resources, leaving employees more time for higher-level tasks that utilize creativity and strategic thinking, thus serving as a basis for organizational innovation (Raisch & Krakowski, 2021; Rožman et al., 2023). However, to fully exploit the benefits of GenAI, traditional workflows need to be rethought (Dasgupta & Wendler, 2019).

Integrating GenAI into organizational life demands a cultural paradigm shift, as GenAI reshapes organizational norms and values, fostering a culture that supports innovation and ethical decision-making (Murire, 2024). The advantage of an adaptive organizational culture is that GenAI solutions can be integrated more efficiently, thereby making companies more resilient to the challenges brought by digital transformation (Menzies et al., 2024).

As can be seen, with the development of generative artificial intelligence, a multitude of new, previously inaccessible opportunities have opened up for SMEs. Our research question is therefore highly topical, examining how generative artificial intelligence influences the operational efficiency and competitiveness of small and medium-sized enterprises in light of the aforementioned factors (automation, training, and organizational transformation).

Materials and Methods

The aim of the present study is a comprehensive examination of the impact of GenAI on the SME sector, with particular regard to efficiency and performance. To answer the research question, we applied a systematic literature review method, structuring the research according to the guidelines of the PRISMA 2020 protocol (Page et al., 2021). The PRISMA 2020 protocol ensured the transparency of the research process, reduced selection bias, and supported the reproducibility of the review. The sources used for conducting the research originate from the Web of Science (WoS) and Scopus scientific databases, queried between January 2, 2026, and January 15, 2026, in the management and business categories. Web of Science and Scopus were selected because they provide broad coverage of peer-reviewed journal articles and conference proceedings in management, business, information systems, and technology-related research, while also supporting transparency and reproducibility through structured indexing. Nevertheless, restricting the search to these two databases may have led to the omission of relevant studies indexed elsewhere, including other academic databases, practitioner-oriented sources, or grey literature. This limitation is especially important in the rapidly evolving field of GenAI. Accordingly, the conclusions of this review should be interpreted as reflecting the systematically indexed peer-reviewed literature available in WoS and Scopus, rather than the full universe of publications on GenAI adoption in SMEs. To conduct the research, we reviewed English-language journal articles and conference proceedings published between 2021 and 2026. During the search in the databases, we used the following syntax: 'TITLE-ABS-KEY / TS =(("Generative AI" OR "GenAI" OR "Generative Artificial Intelligence" OR "Large Language Model*" OR "LLM*") AND ("SME*" OR "Small and Medium Enterprise*" OR "Small and Medium-sized Enterprise*" OR "Small Business*" OR "Start-up*" OR "Startup*") AND ("Adoption" OR "Innovation" OR "Performance" OR "Efficiency" OR "Productivity" OR "Driver*" OR "Implementation"))'. Figure 1 presents the PRISMA flow diagram summarizing the screening and selection process.

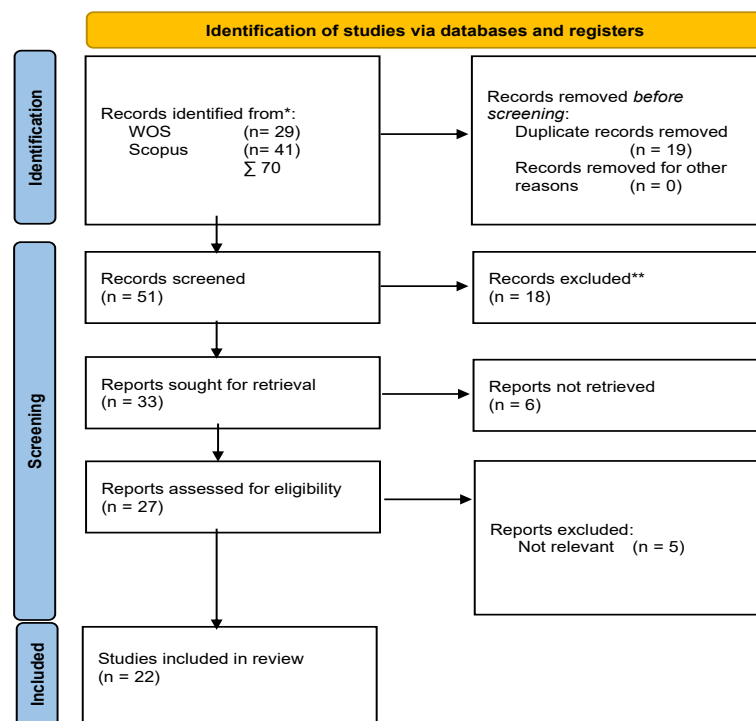


Figure 1. PRISMA Flow Diagram

Using the search string and filters described above, we identified 70 relevant records. Following the methodology of the systematic literature review, we classified our hits according to relevance. As a first step, 19 duplicates were removed. In the next step, a manual analysis of the remaining hits followed, where after reading the abstracts, we excluded 18 hits. As the third step, the retrieval of the remaining literature from various databases followed, where we did not have sufficient access to 6 studies, so these were also excluded from the research. In the final stage, we reviewed the full-text articles and excluded an additional five sources due to relevance concerns. As a final result, 22 sources met the screening requirements. This sample reflects the novelty of GenAI and the still-emerging nature of SME-related GenAI research. Accordingly, the findings should be interpreted as a structured synthesis of peer-reviewed studies indexed in Web of Science and Scopus. The PRISMA protocol supported transparency and helped exclude speculative or non-relevant sources.

To provide a clearer overview of the reviewed literature, the 22 selected studies were grouped according to their primary thematic focus. As shown in Table 1, the studies cluster around three main dimensions: automation and operational efficiency, training and human competencies, and organizational transformation, leadership, and strategic fit.

Table 1. Classification of the 22 Reviewed Studies by Primary Thematic Focus

Automation and Operational Efficiency	Training and Human Competencies	Organizational Transformation, Leadership, and Strategic Fit
Csaszar, Ketkar, & Kim (2024)	Liu & Wang (2024)	Etemad (2024)
Szenftner, Stumpp, & Knopf (2024)	Salminen, Pyykkönen, & Salminen (2024)	Rajaram & Tinguely (2024)

Automation and Operational Efficiency	Training and Human Competencies	Organizational Transformation, Leadership, and Strategic Fit
Bahaw et al. (2025)	Shen & Lin (2024)	Al-Kfairy (2025)
Cho et al. (2025)	Shore et al. (2024)	Donaldson, Linton, & Bendickson (2025)
Ekrokpe, Jayawickrama, & Butun (2025)	Ara & Pandey (2025)	Peñarroya-Farell et al. (2025)
Metzger, O'Reilly, & Mac An Bhaird (2025)	Donaldson, Linton, McDowell, & Bendickson (2026)	Wang & Zhang (2025a)
Rezazadeh et al. (2025)	Mota et al. (2026)	Wang & Zhang (2025b)
Triando et al. (2025)		

The studies were grouped according to their primary thematic focus and arranged within each category first by publication year and then alphabetically by the first author's surname. Some studies could be associated with more than one thematic category; however, each study is listed only once to keep the classification compact, readable, and suitable for inclusion in the systematic literature review section.

Findings

During the systematic literature review, it became evident that the impact of GenAI on the competitiveness and efficiency of SMEs is not linear but prevails along three closely interrelated dimensions. These three dimensions are automation, training (human competencies), and organizational transformation, as mentioned in the theoretical section. In the following, we detail our study results along these dimensions.

Automation and Operational Efficiency

For SMEs, automation represents the primary entry point toward digitalization and achieving operational efficiency. The literature consistently outlines the tendency that GenAI improves operational efficiency fastest through the automation of routine, information-intensive processes. In marketing and sales processes, generative content creation and personalized communication reduce sales cycle time and costs (Rezazadeh et al., 2025; Szenftner et al., 2024), while rapid experimentation supports the fine-tuning of market fit. Szenftner et al. (2024) demonstrated that in the case of small marketing teams, the organizational integration of GenAI tools results in an average time saving of 30-40%. In financial management, GenAI-based solutions are capable of giving early warnings and providing diagnostic support, which, through faster identification of problems, not only increases decision speed but also mitigates error costs (Metzger et al., 2025). This possibility enables SMEs to proactively manage liquidity risks without expensive consultants. The spread and practical utilization of GenAI applications are also supported by text mining analyses exploring technological trends, especially in the fields of generative content creation and predictive analytics (Cho et al., 2025).

The decision-support dimension of automation (summarization, generation of alternatives, scenario building) connects to operational efficiency through the improvement of management quality (Ekrokpe et al., 2025; Csaszar et al., 2024). The OS-matrix developed by Cho et al. (2025) lists which GenAI applications provide targeted solutions to the challenges most pressing for SMEs. This is particularly useful

for alleviating labor shortages and administrative burdens, which are among the most critical challenges for SMEs. Al-Kfairy (2025) also proposes a solution for the lack of funds in SMEs; he sees the realization of GenAI-related automation in capital-constrained companies via the use of cloud-based, instantly integrable "off-the-shelf" services, which cost-effectively ensure the benefits provided by artificial intelligence and are scalable according to needs.

However, exploiting the opportunities offered by automation is not a spontaneous process but requires conscious intervention. Several studies emphasize the dark side of GenAI and the necessity of risk management. The most common risks occurring in GenAI application include hallucination observable in customer service chatbots and text generation, misinformation, data privacy and reputational risk, as well as technological dependence, especially in SMEs with limited resources (Mota et al., 2026; Rajaram & Tinguely, 2024). Triando et al. (2025) highlight precisely for this reason that although GenAI accelerates product development, in early-stage, resource-poor teams, checking hallucinations and code quality can place a disproportionately large burden on developers, which may reduce net efficiency gains. Reviews discussing strategic integration therefore highlight human-in-the-loop operation, the incorporation of control points, the assignment of responsibilities, and the minimum requirements of AI governance (Al-Kfairy, 2025). Investigations with a sustainability focus also indicate that responsible use (data management, transparency, quality assurance) is one of the prerequisites for long-term competitiveness (Ara & Pandey, 2025; Bahaw et al., 2025).

Training and Human Competencies

The key to realizing GenAI benefits is the capability-based approach, as technological tools alone do not replace digital and analytical competencies but require new skills. In financial and operational applications, organizational readiness (data quality, digitalization, documentation of processes) and user competence determine whether GenAI truly supports decision-making and intervention (Metzger et al., 2025). In the startup environment, recurring elements among the determinants of GenAI usage include leadership attitude, team competence, and experimentation capability, which together increase the actual utilization of the technology (Donaldson et al., 2026; Rezazadeh et al., 2025).

Results exploring technological trends identify the development of digital competence and management quality as one of the most important mediating mechanisms of competitiveness and suggest prototype-based, iterative learning as an implementation strategy (Cho et al., 2025). The organizational learning dimension introduces not merely training, but new mechanisms for division of labor and knowledge sharing. GenAI yields stable performance gains if employees are capable of critically evaluating the model's output and feeding it back into corporate knowledge (Ara & Pandey, 2025).

Organizational Transformation, Leadership, and Strategic Fit

Based on the studies, GenAI permanently improves operational efficiency and competitiveness if the introduction is accompanied by organizational transformation: new roles and responsibilities, data and knowledge management, and the redesign of decision-making routines. Research emphasizing the leadership role suggests an approach integrating the composition of the Top Management Team (TMT), leadership cognitive patterns, and corporate resources to explain successful adoption (Peñarroya-Farell et al., 2025). The configurational approach shows that several different pathways can lead to innovation performance through GenAI usage; that is, there is no single best practice, but combinations fitted to the organizational context (Donaldson et al., 2025).

Embedding human-AI collaboration into the innovation process (from ideation to business model development) creates new patterns of organizational learning and creative problem solving (Salminen et al., 2024), which is also supported by the resource-based view: resources related to GenAI become a

competitive advantage when paired with complementary organizational capabilities (Liu & Wang, 2024). In contrast, Mota et al. (2026) draw attention to risks, as inadequate training can lead to cognitive dulling and the loss of critical thinking among employees. Several researchers highlight that, therefore, instead of standardized solutions, strategic integration must be industry- and size-dependent, while the appropriate regulatory environment and the management of organizational changes appear as critical moderators of the process (AI-Kfairy, 2025; Rajaram & Tinguely, 2024).

Future Trends

Based on the synthesis of studies included in the research, GenAI strengthens SME competitiveness through four channels: (1) cost and time advantages via automation, (2) better decision quality and faster adaptation with decision support systems, (3) innovation performance and business model renewal through the realization of the learning organization concept, and (4) resilience and sustainability performance. In crisis situations, GenAI usage can also strengthen entrepreneurial resilience if leaders use the technology for rapid information processing and expanding decision options (Shore et al., 2024).

In the case of internationalization and green innovation, GenAI can connect to performance through supply chain innovations and the development of regulatory compliance (Wang & Zhang, 2025a), while results examining sustainability indicate that besides the perception of utility and usability, embedding into organizational processes decides whether GenAI contributes to triple bottom line goals (Bahaw et al., 2025). Etemad (2024) highlights that GenAI drastically reduces the costs and information barriers of entering the international market. In the context of production systems and business model innovation, GenAI contributes to performance through strengthening exploitative (process optimizing) and exploratory (innovating) learning processes (Wang & Zhang, 2025b), which embodies the longer-term, renewal dimension of competitiveness. Finally, Rezazadeh et al. (2025) highlight that startups can be put on a scalable growth path in a resource-constrained environment with the help of GenAI.

Discussion and Implications

The objective of the present study was to examine how GenAI influences the operational efficiency and competitiveness of SMEs in light of automation, training, and organizational transformation. Based on the comparison of results, it can be stated that GenAI fundamentally rewrites the rules of competitiveness in the SME sector, enabling a qualitative leap from automated execution to augmented innovation.

The Automation Paradox

While previous literature often placed cost reduction at the center, our analysis (Szenftner et al., 2024; Metzger et al., 2025) reveals that mere efficiency improvement serves only as an entry level for competitiveness today. Resources released through automation (time, human capacity) do not create value in themselves if they are not reallocated to strategic activities. SMEs that get stuck at the level of the operational stabilizer (Peñarroya-Farell et al., 2025) become vulnerable in the long term to disruptive market effects, while their competitors using technology for innovation, the strategic adopters, pull ahead. This supports the view that automation is a necessary foundation for competitiveness, but sustainable advantage depends on how effectively firms redeploy freed resources at the organizational level.

The Strategic Appreciation of the Human Factor

One of the most important implications of our research is that the democratization of technology (Metzger et al., 2025; Csaszar et al., 2024) paradoxically increases the value of human competencies. Since GenAI tools become widely and cheaply available (AI-Kfairy, 2025), technological access ceases to be a differentiating factor. The new source of competitive advantage will be absorptive capacity and proactivity

(Donaldson et al., 2026). The results of Shore et al. (2024) and Rajaram & Tinguely (2024) coincide in that resilient and competitive SMEs are those that invest in developing employees' AI literacy and creating a trust-based, experimenting culture. Without managing the risks (cognitive dulling) revealed by Mota et al. (2026), technology implementation can become counterproductive, indicating the strategic necessity of the human-in-the-loop approach (Salminen et al., 2024; Ara & Pandey, 2025). Shen and Lin's (2024) model on AI support for socialization, externalization, combination, and internalization (SECI) processes forms a bridge between the risk of cognitive dulling identified by Mota et al. (2026) and the resilience mentioned by Shore et al. (2024). In the context of the present study, this suggests that competitive SMEs do not merely use GenAI-generated answers but integrate them into the organizational learning cycle, so the technology does not replace but amplifies employees' knowledge.

Organizational Transformation

Overall, GenAI has emerged as a key tool enabling SMEs to adapt to a volatile, uncertain, complex, and ambiguous (VUCA) environment. The results of prior studies (Wang & Zhang, 2025; Rezazadeh et al., 2025) suggest that GenAI enables SMEs to build large-enterprise capabilities (e.g., predictive analytics, global marketing, sustainable innovation) without inheriting their massive cost structure. Following Etemad (2024), GenAI can function as a democratizer of internationalization for SMEs. Market research, translation, and localization capabilities previously available only to large enterprises (Metzger et al., 2025) are now accessible to the smallest SMEs. This rewrites traditional internationalization models; at the same time, the warning by Triando et al. (2025) about early-stage challenges indicates that this process is not risk-free, as the lack of technological maturity in the early phase can lead to critical errors. The adaptation paths presented by Donaldson et al. (2026) and Cho et al. (2025) suggest that successful SMEs are not passive victims but active shapers of digital transformation. The key to future competitiveness is building hybrid intelligence, where automated processes provide stability, prepared human capital ensures creativity, and flexible organizational structure enables continuous strategic renewal.

Conclusion

The objective of this study was to examine how generative artificial intelligence influences the operational efficiency and competitiveness of small and medium-sized enterprises. To address this objective, the study applied a systematic literature review based on the PRISMA 2020 protocol and synthesized peer-reviewed studies indexed in Web of Science and Scopus. The review shows that GenAI affects SME performance through three closely interrelated dimensions: automation, training and human competencies, and organizational transformation.

The findings indicate that GenAI can improve SME efficiency by automating routine and knowledge-intensive tasks, supporting faster decision-making, and reducing operational constraints. However, the review also shows that automation alone is insufficient for sustainable competitiveness. The long-term value of GenAI depends on whether SMEs can develop employee AI literacy, redesign organizational processes, and integrate GenAI into learning, innovation, and strategic decision-making routines. In this sense, GenAI should not be understood merely as a cost-reduction tool, but as a catalyst of organizational renewal and capability development.

The study contributes to the literature by consolidating fragmented research on GenAI adoption in SMEs and by identifying automation, human competencies, and organizational transformation as key mechanisms linking GenAI to operational efficiency and competitiveness. From a practical perspective, the findings suggest that SMEs should combine technological adoption with employee training, governance mechanisms, and organizational change management in order to realize the full benefits of GenAI.

Several limitations should be acknowledged. First, the review relied only on studies indexed in Web of Science and Scopus. Although these databases provide broad coverage of peer-reviewed literature, this restriction may have excluded relevant studies indexed in other academic databases, practitioner-oriented sources, or grey literature. Second, because GenAI is a rapidly evolving field, the available literature remains relatively limited and may not fully capture emerging applications, sector-specific practices, or recent developments. Third, the conclusions are based on a systematic synthesis of existing studies rather than primary empirical data.

Future research should broaden database coverage by including additional academic databases and complementary sources, such as industry reports and practitioner-oriented publications. Further empirical studies are also needed to validate the findings across different SME sectors, countries, and organizational contexts. In addition, future research could examine how GenAI adoption evolves over time, how SMEs manage risks such as hallucination, data privacy, and cognitive dependency, and how organizational capabilities mediate the relationship between GenAI adoption and long-term competitiveness.

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