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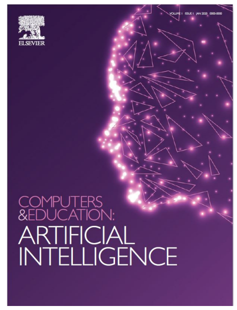

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Toward Understanding the Role of Generative AI in Entrepreneurship Education: A Systematic Review

Abstract: This study presents a systematic literature review to explore the emerging role of Generative Artificial Intelligence (GAI) in entrepreneurship education (EE). While recent years have witnessed an increasing interest in applying GAI tools, such as ChatGPT, to support personalized learning, business model simulation, and decision-making, the field remains at an early exploratory stage. Drawing on 50 peer-reviewed journal articles published between 2019 and early 2025, the study aims to map the conceptual landscape, identify key themes, and assess the current state of theoretical and empirical development. The findings reveal four major domains in GAI-enabled EE: personalized and adaptive instruction, simulation-based entrepreneurial training, ethical and psychological concerns, and ecosystem integration through intelligent systems. Although promising use cases are identified, most studies are either conceptual or limited to small-scale exploratory evidence. As such, the long-term impact of GAI on entrepreneurial competence, mindset, and outcomes remains uncertain and calls for empirical caution. To bridge this gap, this study proposes a set of research propositions and a conceptual framework that integrates micro-level instructional applications with meso-level competency development and macro-level ecosystem readiness. These are grounded in educational theories, including constructivism, experiential learning, and social cognitive theory. In addition, the review suggests methodological strategies, such as structural equation modeling (SEM), hierarchical linear modeling (HLM), and longitudinal mixed-methods designs, to test GAI's influence across cultural and institutional contexts rigorously. Furthermore, the study discusses actionable implications for educators, policymakers, and researchers, emphasizing the importance of ethical guidance, digital equity, and cross-contextual adaptability. It advocates for designing GAI-integrated curricula that foster not only technical proficiency but also critical thinking, creativity, and ethical reasoning. By systematically synthesizing current findings while avoiding overgeneralized claims, this review contributes to clarifying the conceptual boundaries of GAI in EE and sets the foundation for future empirical exploration.

Keywords: Generative artificial intelligence, Entrepreneurship education, Intelligent learning environment, Systematic literature review, Structural equation modeling

1. Introduction

In recent years, the rapid advancement of GAI technologies has profoundly reshaped higher education, enabling more personalized, adaptive, and innovative learning experiences. Large language models (LLMs) such as ChatGPT and DeepSeek, powered by deep learning and massive datasets, demonstrate exceptional language comprehension and content generation capabilities, supporting applications such as intelligent tutoring, personalized feedback, and automated assessment (Arabiat, 2025; Thottoli et al., 2024; Wangsa et al., 2024; Winkler et al., 2023). In the context of EE, GAI presents emerging opportunities to support creativity, decision-making, and experiential learning by enabling the simulation of business scenarios and assisting in strategic planning processes (Bell & Bell, 2023; Chen et al., 2024; Voronov et al., 2023). However, challenges remain, including overreliance on AI tools that may hinder critical thinking and innovation skills (Walczak & Cellary, 2023), uncertainties in instructional integration (Alwaqdani, 2024), and concerns over academic integrity, technological dependence, and data security (Jeremiah, 2025; Voronov et al., 2023). Addressing these issues is critical for effectively leveraging GAI's potential in EE and bridging the gap between current pedagogical practices and the lack of integrated theoretical understanding of GAI's role in EE.

Meanwhile, global economic restructuring and innovation-driven development strategies have positioned EE as a crucial component in cultivating talent for higher education. EE seeks to equip students with innovative thinking, business acumen, and market adaptability to create value in complex business environments (Aithal & Aithal, 2023; Pardo-Garcia & Barac, 2020). Recent studies suggest that EE is gradually moving toward interdisciplinary integration, practice-oriented instruction, and greater use of digital technologies (Mann et al., 2021; Xu, 2024). Universities have enhanced practical training through startup incubators, business competitions, and entrepreneurship labs, while also incorporating massive open online courses (MOOCs), virtual reality (VR), and augmented reality (AR) to improve accessibility and interactivity (Anjum et al., 2020; Greco et al., 2021; Thottoli et al., 2024). Nevertheless, EE still faces persistent challenges, including an overemphasis on theoretical content, insufficient practical training, and a shortage of experienced mentors, which undermine students' entrepreneurial competence and personalized learning experiences (Hameed & Irfan, 2019; Kraus et al., 2019). Additionally, underdeveloped assessment systems make it challenging to quantify entrepreneurial capabilities and optimize teaching methods (Bolzani & Luppi, 2021; Scroccaro et al., 2023). These limitations underscore the importance of further investigating how emerging technologies, particularly GAI, can help address such gaps and potentially support the effectiveness of EE.

In this context, the integration of GAI presents emerging possibilities that may support the development of EE. With its advanced data processing and content generation capabilities, GAI enables educators to provide real-time feedback, supports students in refining business plans and adjusting entrepreneurial strategies, and facilitates entrepreneurship simulations through big data analytics bringing learning experiences closer to real-world business environments while improving business acumen and decision-making skills (T. Nuseir et al., 2020; Thottoli et al., 2024; Zhu & Zhang, 2022). Moreover, AI-powered business simulations, decision optimization, and personalized entrepreneurial support are propelling EE toward intelligence-driven, practice-oriented, and data-informed paradigms (Mavlutova et al., 2020; Shepherd & Majchrzak, 2022; Xu & Sun, 2022). Nonetheless, challenges persist, including concerns over the accuracy of AI-generated content, student overreliance, ethical implications, and the adaptability of teaching practices (Jeremiah, 2025; Walczak & Cellary, 2023). Therefore, a systematic understanding of GAI's role in EE and identifying pathways to optimize its pedagogical integration remain pressing priorities for researchers and practitioners (Chen et al., 2024; Giuggioli & Pellegrini, 2023).

Building on this background, this study systematically reviews the application of GAI in EE, examining its impact on teaching models, the development of students' entrepreneurial capabilities, and the broader educational ecosystem. The review addresses the following research questions: RQ1. What are the primary application scenarios and technological implementations of GAI in EE? RQ2. What instructional designs and teaching strategies have been used to integrate GAI in EE? RQ3. What are the methodological, theoretical, and thematic characteristics of existing research, and what gaps still exist? RQ4. What key variables can be identified to support future empirical studies and theoretical development?

To address these questions, this study employs a systematic literature review (SLR) to synthesize high-quality, peer-reviewed research, identifying key research directions and practical challenges. The specific objectives are to: 1. Systematically gather and evaluate literature with rigorous search strategies and quality standards. 2. Categorize research themes and theoretical frameworks, creating a foundation for future theoretical growth. 3. Identify significant variables related to students' attitudes, intentions, innovation skills, curriculum design, educator roles, and feedback mechanisms for future quantitative studies. 4. Critically examine research gaps and recommend directions for future empirical research.

This study highlights that integrating GAI into EE not only tackles practical and technical challenges but also aligns with constructivist, experiential, and connectivist learning theories, which support learner autonomy, collaboration, and active knowledge building. These pedagogical implications emphasize the importance of designing theory-based, technology-enhanced educational interventions in the digital age. The rest of this paper is organized as follows: Section 2 covers the research methodology. Section 3 shares the findings. Section 4 discusses the current state of research and suggests directions for improvement. Section 5 concludes with key findings, theoretical contributions, practical implications, and recommendations for future research and policy.

2. Methodology

To address the aforementioned research questions, this study adopts the SLR method. SLR is a well-established and widely accepted research tool across multiple academic disciplines, including education, management, and entrepreneurship (Chen et al., 2021; Petticrew & Roberts, 2008; Snyder, 2019). Literature reviews typically follow three main approaches: traditional narrative reviews, meta-analysis, and systematic reviews (Green et al., 2006; Okoli, 2015). Narrative reviews often exhibit high subjectivity and lack methodological rigor, leading to potential coverage gaps and research bias (Petticrew & Roberts, 2008; Snyder, 2019). Similarly, meta-analysis requires highly comparable datasets and advanced statistical tools, making it susceptible to publication bias and heterogeneity issues (Green et al., 2006; Snyder, 2019). Given the emerging nature of GAI in EE, this study adopts SLR to explore its applications and impacts comprehensively. This approach is particularly suitable for examining emerging fields and interdisciplinary research topics (Pickering & Byrne, 2014; Snyder, 2019), which aligns with the characteristics of the intersection between GAI and education.

This study follows an eight-step SLR process: (1) defining research questions, (2) developing the review protocol, (3) searching the literature, (4) screening for inclusion, (5) assessing study quality, (6) extracting relevant data, (7) analyzing and synthesizing findings, and (8) reporting results (Okoli, 2015; Pickering & Byrne, 2014; Snyder, 2019). The review process is guided by three key elements: defining search terms, selecting the dataset, and establishing inclusion criteria. This study adheres to established guidelines from prior rigorous reviews to ensure the transparency and replicability of the SLR process (Banha et al., 2022; Snyder, 2019). The review protocol adheres to best practices by incorporating clear search terms, a well-defined dataset, and stringent screening criteria, thereby ensuring a reproducible and transparent approach (Abelha et al., 2020; Moher et al., 2009; Page et al., 2021).

2.1. Data search

To ensure the comprehensiveness and quality of the literature, this study utilized three of the most influential academic databases globally: Web of Science (WoS), Scopus, and ProQuest. The search strategy was constructed using the keywords "Generative AI", "ChatGPT", "Artificial Intelligence", "Entrepreneurship Education", "Innovation Education", and "Digital Education" to maximize relevant coverage. The inclusion of "Innovation Education" and "Digital Education" alongside "Entrepreneurship Education" reflects the interdisciplinary nature of the field and addresses regional and conceptual variations in terminology. In some contexts, particularly in East Asian and European literature, EE is often discussed under the broader concept of “Innovation and Entrepreneurship Education”, which integrates entrepreneurial skill development with innovation-driven pedagogy. Similarly, the term “Digital Education” was included to capture studies that examine GAI as part of broader digitalization and digital learning initiatives in education, which often encompass entrepreneurship-related contexts. These terms ensured that relevant studies adopting these conceptualizations were not overlooked.

This review covers literature published from January 2019 to January 2025. Although GAI tools like ChatGPT became publicly available in late 2022, earlier studies were included to capture foundational developments in GAI research, such as algorithmic frameworks, theoretical ideas, and early prototypes or pilot applications. These studies offer theoretical and methodological insights that form the basis for current GAI applications in EE and are therefore important for understanding the field’s evolution. Following the initial search, additional screening was applied, including only peer-reviewed journal articles and limiting the language to English. As a result, 370 articles published between January 2019 and January 2025 were retrieved. Table 1 shows the Boolean search formulas and search results used in this study.

Table. 1. Searching queries and results in WoS, Scopus, and ProQuest.

Database	Searching Queries	Searching Results
WoS	TS = (“Generative AI” OR “ChatGPT” OR “Artificial Intelligence”) AND TS = (“Entrepreneurship Education” OR “Innovation Education” OR “Digital Education”) AND DT = (“Article”) AND LA = (“English”)	142
Scopus	TITLE-ABS-KEY (“Generative AI” OR “ChatGPT” OR “Artificial Intelligence”) AND TITLE-ABS-KEY (“Entrepreneurship Education” OR “Innovation Education” OR “Digital Education”) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (PUBSTAGE, “final”))	119
ProQuest	NOFT (“Generative AI” OR “ChatGPT” OR “Artificial Intelligence”) AND NOFT (“Entrepreneurship Education” OR “Innovation Education” OR “Digital Education”)	109

2.2. Data screening and selection

After initially retrieving 370 articles, a deduplication process removed 100 duplicates, leaving 270 articles for further screening. To ensure alignment with the review's scope and objectives, the screening was guided by explicit inclusion and exclusion criteria.

The inclusion criteria required that (1) studies be peer-reviewed journal articles published between 2019 and January 2025, (2) the publication be in English, (3) the content explicitly focus on applying GAI in EE contexts, and (4) the research quality be rated as high or moderate based on standardized evaluation criteria. Conversely, studies were excluded if they met any of the following conditions: (1) being book chapters, conference papers, technical reports, or other non-journal publications, (2) lacking direct relevance to EE or not examining AI’s role in this context, (3) showing weak conceptual alignment with the research objective, or (4) scoring below the moderate-quality threshold in the quality assessment.

After applying these criteria, 181 articles were excluded for being non-journal publications or lacking sufficient relevance to AI in EE. The remaining 89 articles were downloaded and documented in a Microsoft Excel spreadsheet, categorized by data type and subcategories to enhance data management (Snyder, 2019). A full-text review was then conducted on all 89 papers, incorporating both relevance assessment and quality evaluation. Articles that did not directly contribute to the study’s objectives were excluded at this stage. Ultimately, 48 qualified studies were selected, supplemented by two additional papers identified through reference tracking, yielding a final dataset of 50 articles for data extraction and synthesis.

Although some articles mentioned AI or EE in their abstracts, they did not directly examine the application of AI in EE. Instead, they focused on other areas. For instance, certain studies explored AI-driven intelligent tutoring, automated Q&A systems, and student support services in higher education (Okonkwo & Ade-Ibijola, 2021) rather than its role in EE. Similarly, some research has addressed the integration of GAI in teacher professional development, analyzing how educators adapt to AI-driven changes in the classroom. However, it does not discuss EE models or curriculum optimization (Brandão et al., 2024). Other studies focused on the broader impact of AI on education rather than its specific applications in entrepreneurship training. For example, some examined the general adoption of ChatGPT in education but did not analyze its role in entrepreneurial learning practices (Pradana et al., 2023). Likewise, specific research has explored how AI may support student motivation, but it has offered limited discussion on EE’s pedagogical models and instructional strategies (Artemova, 2024). These exclusion criteria ensured a sharper research focus, including only studies that directly addressed AI applications, challenges, and optimization strategies in EE, thereby enhancing the relevance and quality of the literature review.

To further address the ambiguity surrounding the term “Artificial Intelligence” in studies published prior to the emergence of tools such as ChatGPT and DALL-E, we implemented an additional clarification during the full-text review phase. Specifically, studies were retained only if they demonstrated a clear conceptual or technical alignment with the core characteristics of GAI including the use of generative adversarial networks (GANs), LLMs, transformer-based architectures, or neural networks specifically designed for content generation. In contrast, studies that referred to “Artificial Intelligence” in a broad or generic sense without involving generative functionalities were excluded. This screening approach ensured thematic consistency with the objectives of the review. Earlier studies that focused on algorithmic foundations, prototype generative systems, or theoretical frameworks directly relevant to the functionalities later embodied in generative tools were considered eligible for inclusion particularly those published prior to 2022, before the public release of large-scale GAI platforms such as ChatGPT and DALL-E.

During the full-text review, a quality assessment was conducted, a critical step in systematic evaluations that significantly impacts the reliability of research findings (Okoli, 2015; Xiao & Watson, 2019). The assessment focused on the research design and methodology used in each study, applying standardized criteria for evaluation (Bandara et al., 2015; Pluye et al., 2009). Key assessment criteria included whether the study clearly described its methodology, explicitly outlined data collection techniques, and provided a detailed explanation of data analysis procedures (Bandara et al., 2015). Each study was scored based on predefined criteria: 2 points for fully meeting the standards, 1 point for partially meeting them, and 0 points for failing to meet them (Zhang & Ramayah, 2024). Based on the total score, research quality was categorized as high (≥5 points), moderate (3-4 points), or low (<3 points). Only high and moderate-quality studies were included in the dataset, while low-quality research was excluded. In total, 48 qualified studies were selected, along with two additional papers identified through reference tracking, a commonly used method in literature reviews to uncover potentially overlooked studies (Chen et al., 2024; Hennink & Kaiser, 2022). The final 50 articles were included for data extraction and synthesis. The screening and inclusion process is illustrated in Figure 1, while the quality assessment results are provided in Appendix B.

2.3. Data extraction and synthesis

At this stage, the structure of the previously created Excel spreadsheet was modified to assign values and ensure comprehensive documentation of each article’s fundamental information. Following Snyder (2019) recommendations, key elements from the selected studies were extracted and categorized into four primary dimensions: (1) publication details (authors, year, journal, region); (2) applied theories and methodologies; (3) key AI-enabled factors in EE (e.g., personalization, simulation, ethical challenges); and (4) core research findings. To synthesize the findings, we used a thematic synthesis approach.

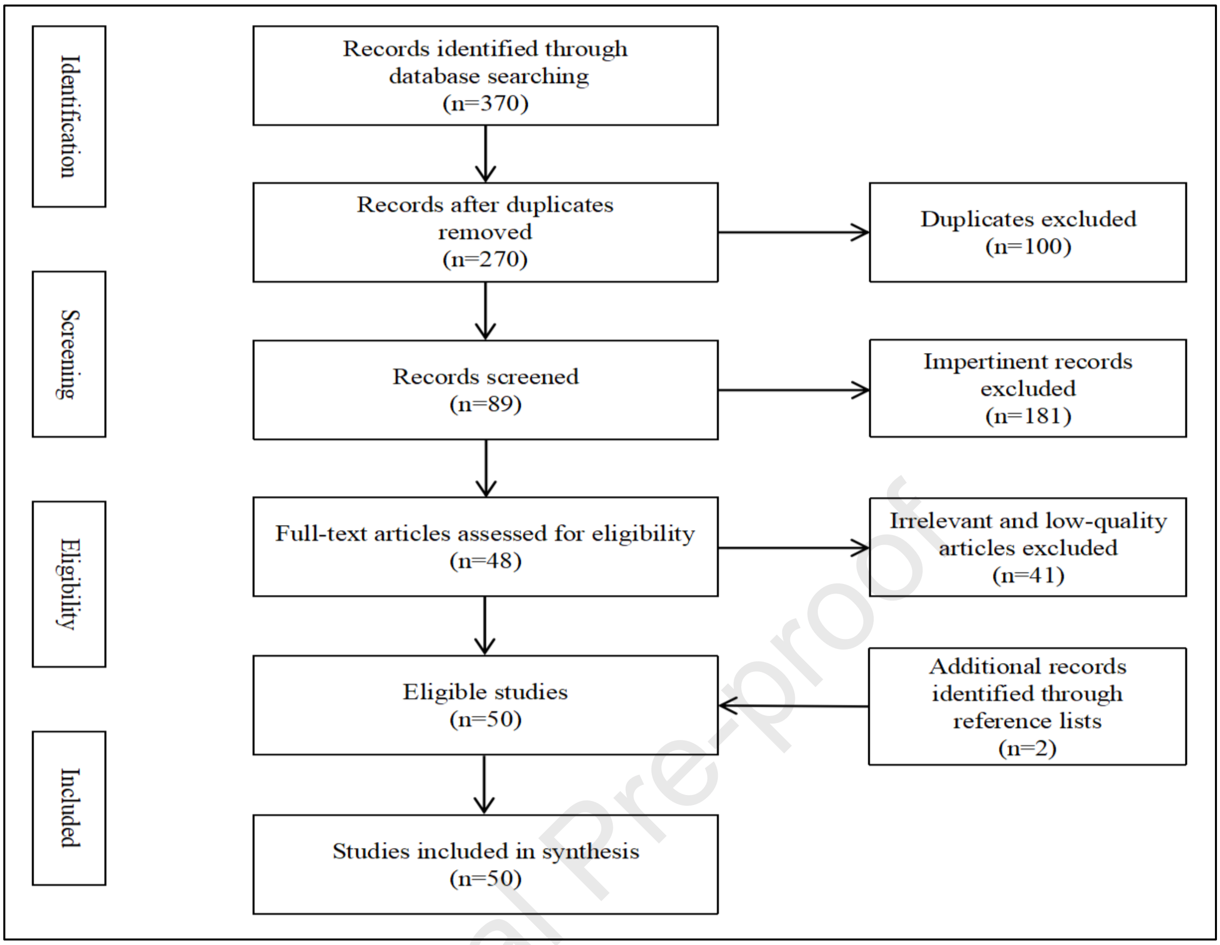

Figure. 1. Article search and selection based on the PRISMA flow diagram

First, a deductive coding scheme was developed to align with the four research questions, classifying the extracted content into predefined conceptual categories, including GAI application domains, instructional strategies, theoretical frameworks, and influencing variables. Then, an inductive coding process was applied to identify emergent patterns and cross-study themes beyond the predefined structure, allowing for grounded insights from diverse studies. The coding process was iteratively refined and reviewed to ensure consistency and reliability. Independent reviewers conducted two rounds of coding to validate inter-coder agreement. To ensure theoretical coherence, the identified themes were cross-referenced with the theoretical frameworks outlined in Section 3, linking empirical findings to conceptual structures. This structured and transparent process enabled the systematic integration of insights across studies. The final mapping scheme used for coding and synthesis is presented in Appendix A, which complements Appendix B by detailing the criteria and variables employed in the literature extraction and thematic categorization process. Together, these appendices support the reproducibility and analytical rigor of the review process.

3. Review findings

This section presents the findings from the systematic literature review on the role of GAI in EE. The analysis is organized around several key dimensions, including bibliographic trends, research methodologies, primary theoretical frameworks, and the main themes explored in the selected studies. By synthesizing insights from 50 academic papers, this review highlights the evolution of AI-driven EE research and identifies important gaps that need further investigation. The findings provide a comprehensive overview of how GAI has been studied, the key areas of focus, and the emerging trends that are shaping the field. The following sections discuss these aspects in detail, starting with an examination of the publication characteristics of the reviewed literature.

3.1. Publication information

This study consolidates key bibliographic details of the selected literature, including research titles, journal names, publication years, and countries or regions of origin. Since the search strategy was limited to studies published after 2018, the earliest included research dates from 2019. Between 2019 and 2021, the number of studies in this field remained relatively low. However, starting in 2022, research output increased significantly, showing a rapid upward trend. Notably, 2024 marked the peak of research activity in this area, with 13 relevant studies included in this review. The distribution of studies by publication year is shown in Figure 2.

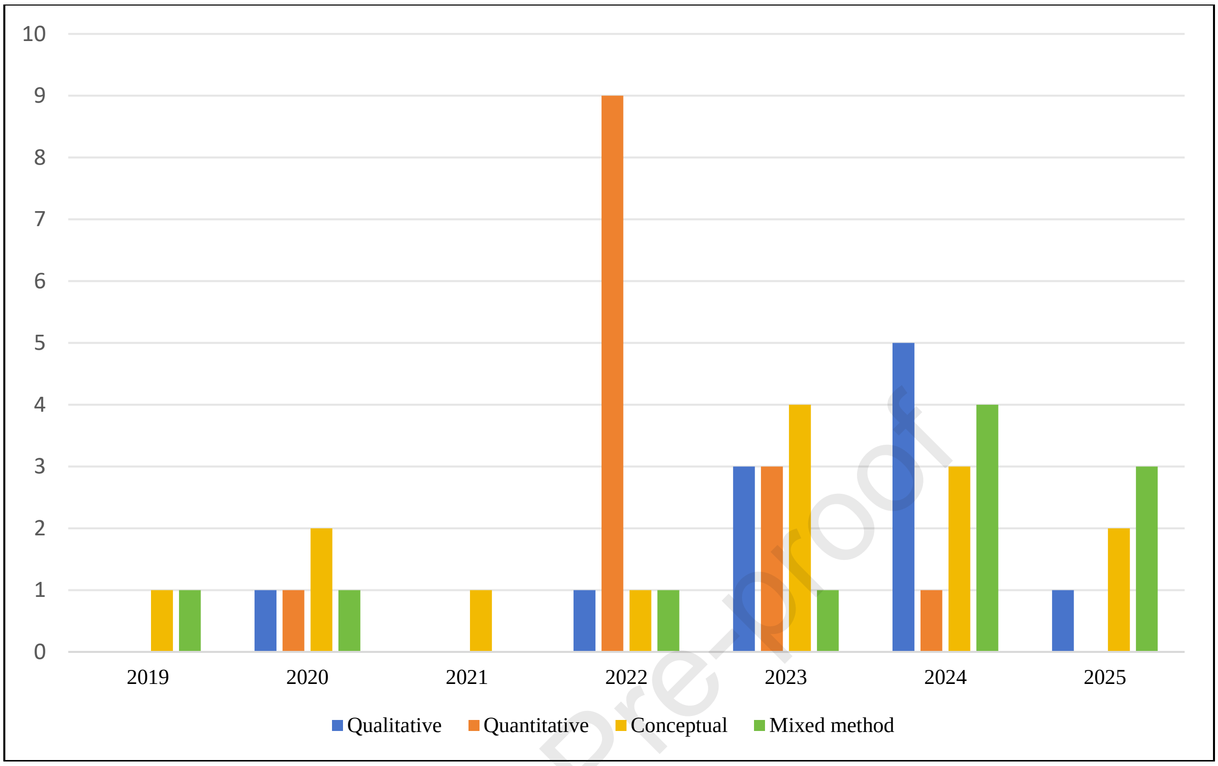

Figure. 2. The number of publications and methodologies used each year.

Regarding publication sources, the 50 selected studies were published across 38 journals, reflecting the interdisciplinary nature of AI-driven EE research. Among these, 19 papers were concentrated in just 7 journals, accounting for 38% of the total sample. The most frequently represented journals include the *Journal of Business Venturing Insights* (4 articles), *Frontiers in Psychology* (4 articles), and the *International Journal of Entrepreneurial Behavior & Research* (3 articles), all of which hold significant academic influence in business and psychology. Additionally, this review incorporates studies from various interdisciplinary fields, including educational management, entrepreneurship research, engineering, and the natural sciences, with notable contributions from journals such as *The International Journal of Management Education*, *Entrepreneurship Theory and Practice*, *Scientific Reports*, and *Applied Sciences*. This distribution indicates that research on AI in EE spans multiple disciplines, engaging with diverse theoretical frameworks, research methodologies, and analytical approaches (Drake & Reid, 2021; Moirano et al., 2020). The overview of journal distribution is presented in Figure 3.

Regarding geographical distribution, the 50 reviewed studies originate from 23 countries, highlighting the global interest in AI-driven EE. Research output is primarily concentrated in China and the United States, accounting for nearly half of the publications. China leads with 14 studies, reflecting its strong governmental support for AI integration in education and entrepreneurship. The United States follows with nine publications, underscoring its established research infrastructure and focus on technological innovation in EE. European countries, including the United Kingdom, Germany, Poland, and Latvia, make significant contributions to the field, particularly in exploring the adoption of AI in business and education. Notably, the presence of studies from Australia, Thailand, and the United Arab Emirates suggests a growing interest in AI-driven EE beyond traditionally dominant regions. However, contributions from developing economies remain limited, indicating potential research gaps regarding the accessibility, implementation, and effectiveness of AI-enabled EE across diverse socio-economic contexts. The global distribution of studies is visualized in Figure 4, illustrating the concentration of research efforts and identifying regions with emerging interest in AI-driven EE. This geographical analysis offers valuable insights into how AI adoption in EE varies across different institutional, cultural, and policy environments, paving the way for future cross-national comparative research.

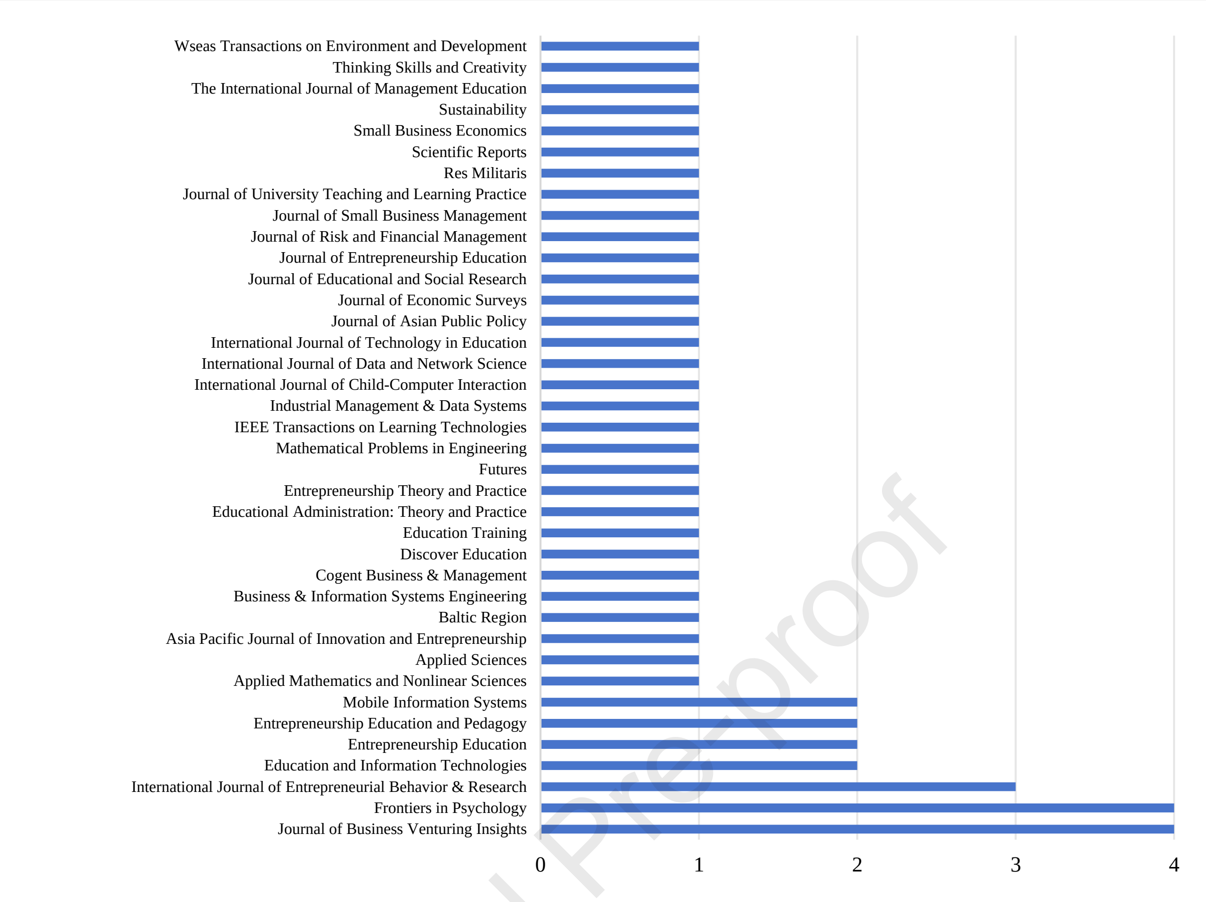

Figure. 3. Distribution of publications across journals.

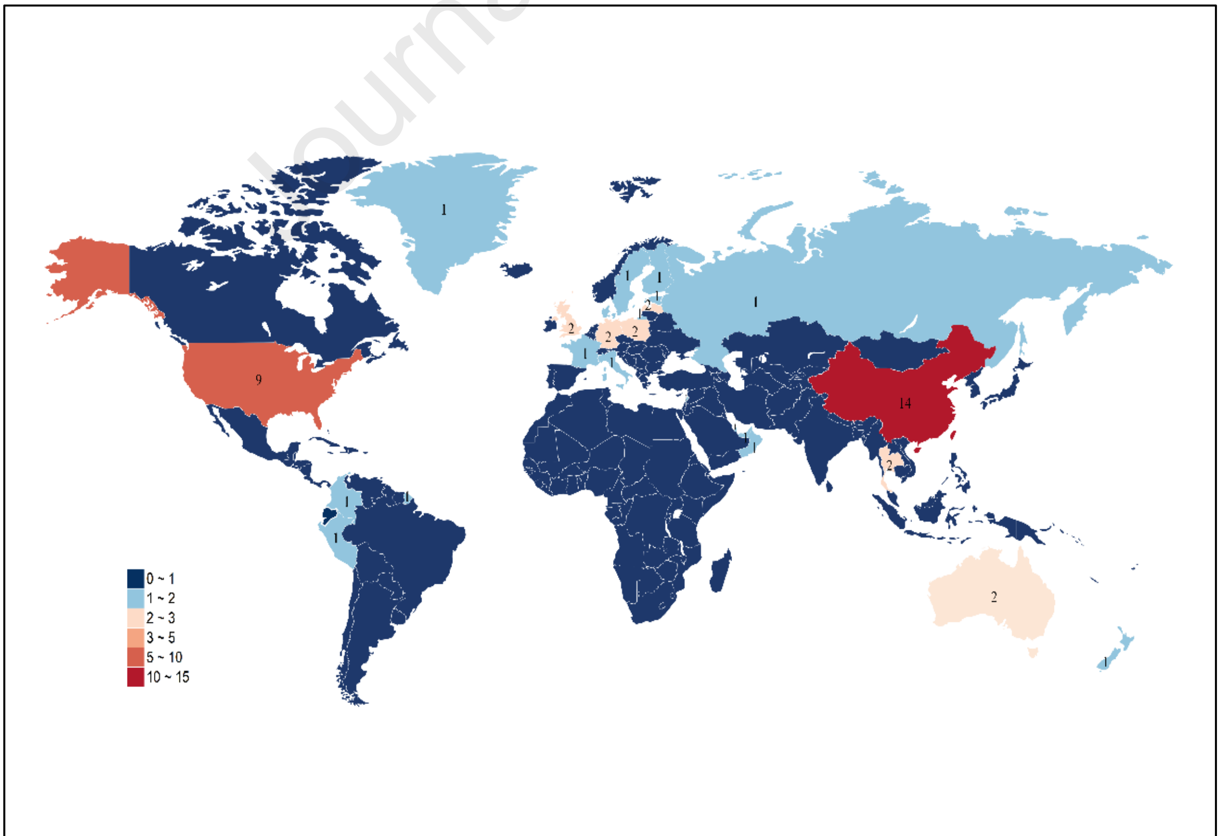

Figure. 4. Geographical distribution of studies on generative ai in entrepreneurship education.

3.2. Applied theories and frameworks

Analyzing the theories and frameworks adopted in existing studies provides a clearer understanding of the research foundations of AI in EE. It provides a structured overview of the research foundations of AI in EE, facilitating a deeper understanding of theoretical applications (Secundo et al., 2024). Among the 50 analyzed studies, 13 explicitly stated their theoretical foundation, with the Theory of Planned Behavior (TPB) being the most frequently utilized framework, appearing in 5 studies. Other theoretical frameworks were scattered across different research contexts, as detailed in Table 2. Upon further categorization, the application of theoretical frameworks in the reviewed literature aligns with three primary pathways: individual behavior and technology adoption theories, ecosystem and multi-stakeholder collaboration theories, and learning, cognition, and technological performance theories. These perspectives examine decision-making in EE, technology adoption and integration, and the collaborative mechanisms among stakeholders in AI-driven EE.

Table. 2. Theories/frameworks underpinning research.

Theories and frameworks	Frequency	Author(s)/Year
Theory of Planned Behavior	5	T. Nuseir et al. (2020); Kang (2022); Zhu and Zhang (2022); Dabbous and Boustani (2023); Lesinskis et al. (2023)
Technology Acceptance Model	1	Alqahtani (2023)
Causal Attribution Theory	1	Liu et al. (2025)
Cognitive Neuro-Fuzzy Model	1	Tkachenko et al. (2019)
Connectivism Learning Framework	1	Liang and Bai (2024)
Entrepreneurial Ecosystem Theory	1	Roundy and Asllani (2024)
External Enablement Framework	1	Davidsson and Sufyan (2023)
Mode of Entrepreneurship Attitude	1	Chen et al. (2022)
Technology to Performance Chain Framework	1	Marchena Sekli and Portuguez-Castro (2025)

The TPB is the core theoretical framework in the individual behavior and technology adoption pathway. TPB explains behavioral intention through attitude, subjective norms, and perceived behavioral control, making it a widely applied theory in EE to examine how entrepreneurial courses influence students' decision-making (Ajzen, 1991; Bosnjak et al., 2020). Studies utilizing TPB have associated AI-driven personalized EE with improvements in students' entrepreneurial intention and capabilities by strengthening these three psychological factors (Dabbous & Boustani, 2023; Kang, 2022; Lesinskis et al., 2023; T. Nuseir et al., 2020; Zhu & Zhang, 2022). Several studies extend TPB by integrating additional theoretical dimensions to provide a more comprehensive understanding of AI's impact on EE. For instance, Dabbous and Boustani (2023) combined TPB with Social Support Theory to explore how AI-generated performance expectations influence entrepreneurial intention through perceived behavioral control. T. Nuseir et al. (2020) incorporated Entrepreneurial Self-Efficacy (ESE) into TPB, demonstrating that AI-driven EE supports self-efficacy, indirectly strengthening students' entrepreneurial intentions. Similarly, Alam et al. (2019) extended TPB using the Mode of Entrepreneurship Attitude (MEA) framework. Chen et al. (2022) further applied MEA to examine how students' attitudes toward entrepreneurship evolve, analyzing the dynamic relationship between attitude and behavioral intention. Beyond TPB, other technology adoption models have been applied to AI-enabled EE. The Technology Acceptance Model (TAM) and Causal Attribution Theory (CAT) provide additional insights into technology adoption and learning behavior. Alqahtani (2023) expanded TAM to develop a multidimensional measurement framework for AI adoption in EE, emphasizing perceived usefulness and ease of use as key factors influencing AI adoption. Using CAT, Liu et al. (2025) proposed an AI-driven framework for optimizing entrepreneurial education, which leverages AI and data analytics to help students better understand entrepreneurial failure, refine their learning experiences, and support entrepreneurial competence.

Researchers focus on policy support, resource integration, and multi-party cooperation mechanisms in advancing EE in the ecosystem and multi-stakeholder collaboration pathway. Studies in this domain have adopted the Entrepreneurial Ecosystem Theory (EET) and the External Enablement Framework (EEF). Traditionally, EET emphasizes the collaborative mechanisms among universities, governments, and enterprises, as well as their role in integrating resources for the development of entrepreneurial projects. Roundy and Asllani (2024) incorporated elements of technological innovation theory into this framework, exploring how AI, as part of the entrepreneurial ecosystem, may support resource accessibility and utilization efficiency. Similarly, Davidsson and Sufyan (2023) expanded this perspective by integrating key elements of the dynamic capability theory into EEF. Their study examined how AI might contribute to entrepreneurs' adaptability, decision-making efficiency, and market responsiveness, thereby enriching theoretical discussions on AI-driven EE.

In the learning cognition and technological performance pathway, researchers focus on the role of AI tools in enhancing learning effectiveness and entrepreneurial performance. The Cognitive Neuro-Fuzzy Model combines cognitive learning theories and fuzzy logic to explore how AI may optimize personalized learning pathways in unstructured EE environments and improve students' decision-making abilities through adaptive regulation mechanisms (Tkachenko et al., 2019). Liang and Bai (2024) incorporated GAI-driven interactive learning environments into the Connectivism Learning Framework to help students construct knowledge networks within virtual entrepreneurship simulations, reducing practical barriers and enhancing learning outcomes. Meanwhile, Marchena Sekli and Portuguez-Castro (2025) extended the Technology to Performance Chain Framework, integrating technology fit and task compatibility as key variables to develop a multi-level evaluation system tailored to the requirements of entrepreneurial tasks. Some studies have explored the potential mediating role of GAI in entrepreneurial task completion and performance outcomes, suggesting that AI's ability to personalize learning and optimize decision-making may contribute to improved entrepreneurial performance.

In summary, the theoretical frameworks reviewed above collectively offer complementary perspectives on the role of GAI in EE. Specifically, TPB and related behavioral theories describe individual-level psychological and behavioral mechanisms. EET and EEF, on the other hand, highlight organizational and ecosystem-level factors. Learning cognition theories (e.g., Cognitive Neuro-Fuzzy Model, Connectivism, Technology-to-Performance Chain) examine cognitive processes, knowledge construction, and task performance outcomes. Instead of relying on a single overarching guiding framework, this multi-theoretical approach reflects the interdisciplinary and emergent nature of the field, providing a more nuanced and comprehensive conceptual foundation. This integrative perspective guides the subsequent analysis and discussion by connecting empirical findings with distinct yet interconnected theoretical lenses.

3.3. Types of methods used

An analysis of the 50 reviewed studies shows a relatively even distribution of research methods across quantitative, qualitative, mixed-methods, and conceptual research. As shown in Figure 5, 14 studies (28%) used quantitative methods, 11 studies (22%) employed qualitative approaches, another 11 studies (22%) utilized mixed-methods, and 14 studies (28%) were conceptual. This distribution balances theoretical exploration with empirical analysis, indicating that researchers focus on developing theoretical frameworks and data-driven empirical studies.

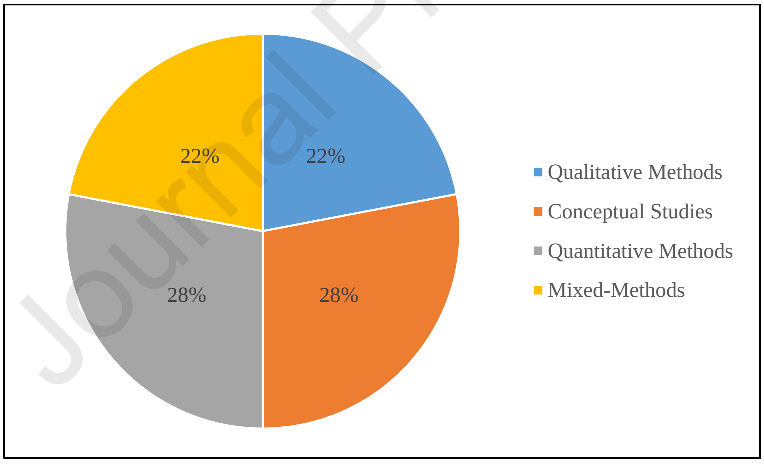

Figure. 5. Research methodology chart.

From a temporal perspective, the period from 2019 to 2021 saw a dominance of conceptual studies, where researchers primarily employed theoretical modeling, case studies, and interviews to explore the applications and impacts of AI in EE. During this period, research focused on theoretical development and framework exploration, covering areas such as entrepreneurial decision support, personalized learning pathways, cognitive training enhancement, and the interplay between technology and human judgment (Chalmers et al., 2021; Kleine et al., 2020; T. Nuseir et al., 2020; Tkachenko et al., 2019; Townsend & Hunt, 2019). The year 2022 marked a significant rise in quantitative research, with a notable increase in studies employing quantitative methods, reaching nine studies and surpassing other research methodologies. This shift may be attributed to the deepening integration of AI technology in EE, prompting researchers to extensively utilize survey-based studies, experimental research, and machine learning models to quantify the impact of AI-driven EE on students' entrepreneurial confidence, intentions, and attitudes. For instance, studies have analyzed how AI supports students' entrepreneurial self-confidence (Kang, 2022), examined AI's influence on students' entrepreneurial capabilities and intentions (Zhu & Zhang, 2022), and validated AI's positive impact on university students' entrepreneurial attitudes (Chen et al., 2022). These studies have made meaningful contributions to the early development of empirical research on AI in EE, providing a foundation for further exploration.

Since 2023, research themes have expanded further, and the distribution of methodologies has become more balanced, with quantitative, qualitative, conceptual, and mixed-methods research appearing in nearly equal proportions. The research focus has also broadened from AI applications in teaching to a more comprehensive analysis of entrepreneurial capability development, business model innovation, and entrepreneurial ecosystems. For example, Giuggioli and Pellegrini (2023) employed qualitative research to investigate how AI supports entrepreneurship through opportunity recognition, decision-making support, and business performance optimization. Roundy and Asllani (2024) extended the Entrepreneurial Ecosystem Framework, incorporating AI as a key component in entrepreneurial ecosystems. Using a mixed-methods approach, Torres Ortega et al. (2025) highlighted the advantages of GPT-4 in EE, emphasizing personalized learning and motivational enhancement as key factors in entrepreneurial competence development.

As research themes expand, methodological diversity has also increased. In qualitative research, interviews, observations, and textual analysis are commonly used for data collection, while content analysis, thematic analysis, discourse analysis, and case studies have been applied across various research contexts (Darnell & Gopalkrishnan, 2024; Hammoda, 2024; Kleine et al., 2020; Liang & Bai, 2024; Voronov et al., 2023; Weng et al., 2025). These approaches support the depth of understanding regarding AI's role in EE, offering insights into learning experiences and the entrepreneurial process. Regarding analytical tools, three qualitative studies utilized NVivo and Excel for text analysis, though most still relied on manual coding. For quantitative and mixed-methods research, studies primarily employed SPSS, AMOS, SmartPLS, Python, MATLAB, and R for data modeling and statistical analysis. Among these, six studies used t-tests, while other commonly employed methods included SEM (5 studies), machine learning approaches (3 studies), regression analysis (3 studies), ANCOVA (1 study), reliability and validity analysis (1 study), Chi-square tests (1 study), and exploratory factor analysis (1 study).

3.4. Keyword co-occurrence analysis

To identify the core themes and conceptual frameworks in AI-driven EE research, this study employs VOSviewer for keyword co-occurrence analysis. VOSviewer is widely utilized in bibliometric analysis to visually represent the structure, research hotspots, and dynamic evolution of academic fields (Blanco-González-Tejero et al., 2023; Ding & Yang, 2022; Pradana et al., 2023). Figures 6 and 7 visually illustrate the keyword co-occurrence network and its temporal changes, revealing the key research directions and trends within this domain. In keyword co-occurrence analysis, the frequency of co-occurrence is determined by the frequency with which keywords appear together in article titles, abstracts, or author-provided keyword lists (Van Eck & Waltman, 2010). This analytical approach reveals the relationships between research topics and concepts, mapping the overall research structure and its evolutionary trajectory (Van Eck & Waltman, 2017). This study analyzed 50 selected papers, extracted 167 keywords, and set a minimum co-occurrence threshold of 2, ultimately identifying 26 core terms (Figure 6). According to Van Eck and Waltman (2017), the recommended minimum threshold for keyword co-occurrence is typically 3. However, due to this study's relatively tiny keyword dataset (167 terms), applying a threshold of 3 would exclude some low-frequency but potentially significant keywords, limiting the comprehensive identification of research themes. To mitigate this issue, this study adopts a more inclusive threshold (co-occurrence ≥ 2) to ensure the incorporation of meaningful concepts, reveal a richer research landscape, and minimize analytical bias resulting from a limited dataset (Ibekwe et al., 2021; Lazăr, 2022).

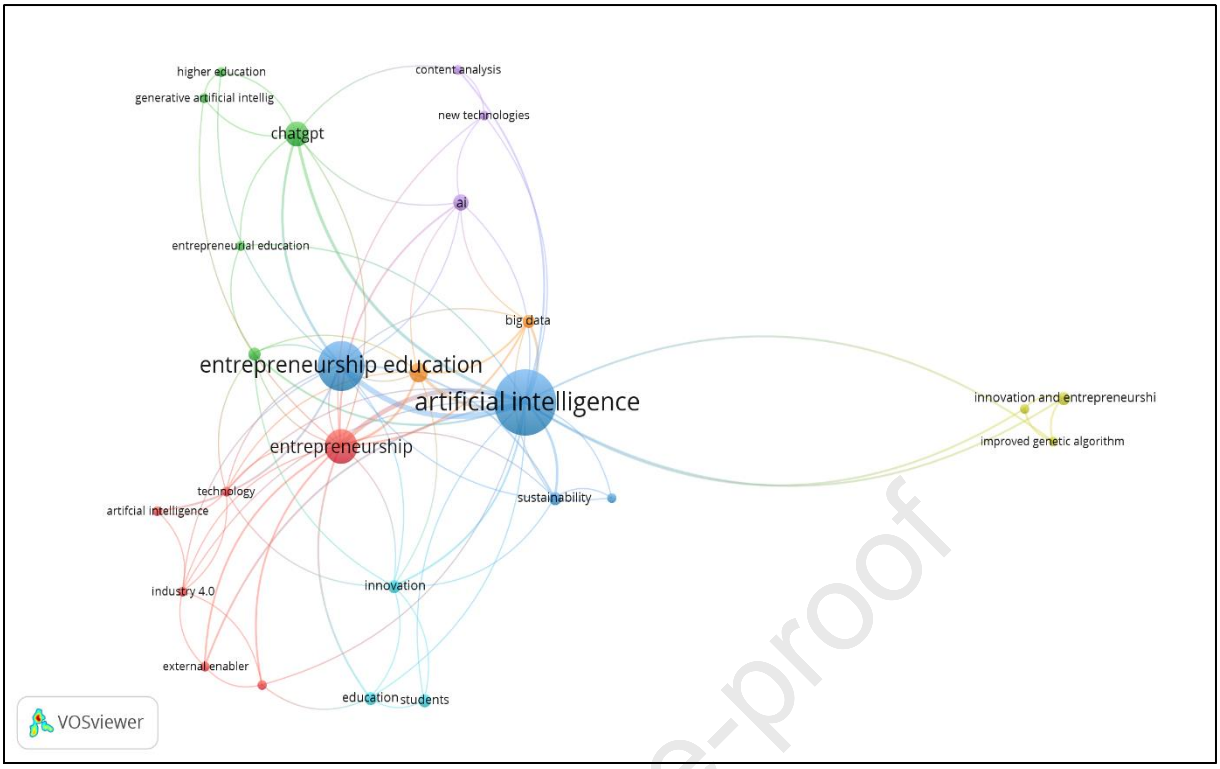

Figure. 6. Co-assurance (Keywords).

In the visualized co-occurrence network, the size of the nodes represents the frequency of keyword appearances, the color indicates the cluster to which each node belongs, and the links between nodes reflect the degree of association between keywords. The length and thickness of the links further illustrate the strength of the relationships between keywords (Blanco-González-Tejero et al., 2023; Pradana et al., 2023; Van Eck & Waltman, 2017). These keywords highlight the core research themes in AI-enabled EE. Among them, “artificial intelligence” (26 occurrences), “entrepreneurship education” (18 occurrences), “entrepreneurship” (11 occurrences), and “ChatGPT” (7 occurrences) appeared most frequently. Based on co-occurrence patterns, the analysis identifies three primary clusters. The red cluster focuses on AI and technology-driven entrepreneurship, including keywords such as “technology”, “artificial intelligence”, “industry 4.0”, “external enabler”, and “opportunity”. Studies in this cluster examine how AI functions as an external enabler, fostering technology-driven entrepreneurship, increasing entrepreneurial success rates, and optimizing the entrepreneurial ecosystem. The blue cluster emphasizes EE and sustainability, with keywords such as “entrepreneurship education”, “sustainability”, “education students”, and “innovation”. Research in this cluster explores AI’s role in advancing EE, particularly in promoting sustainable entrepreneurship and fostering innovation. The green cluster revolves around the application of GAI in EE, with key terms including “ChatGPT”, “generative artificial intelligence”, “higher education”, and “entrepreneurial education”. This cluster examines how AI facilitates personalized learning and delivers more precise learning feedback. Overall, the keyword clustering analysis reveals the structural framework of AI research in EE. The research focus has evolved dynamically, shifting from AI as a technological enabler for entrepreneurship to developing EE systems and, subsequently, integrating GAI with personalized learning. This evolution reflects the ongoing development and broadening of research in this field.

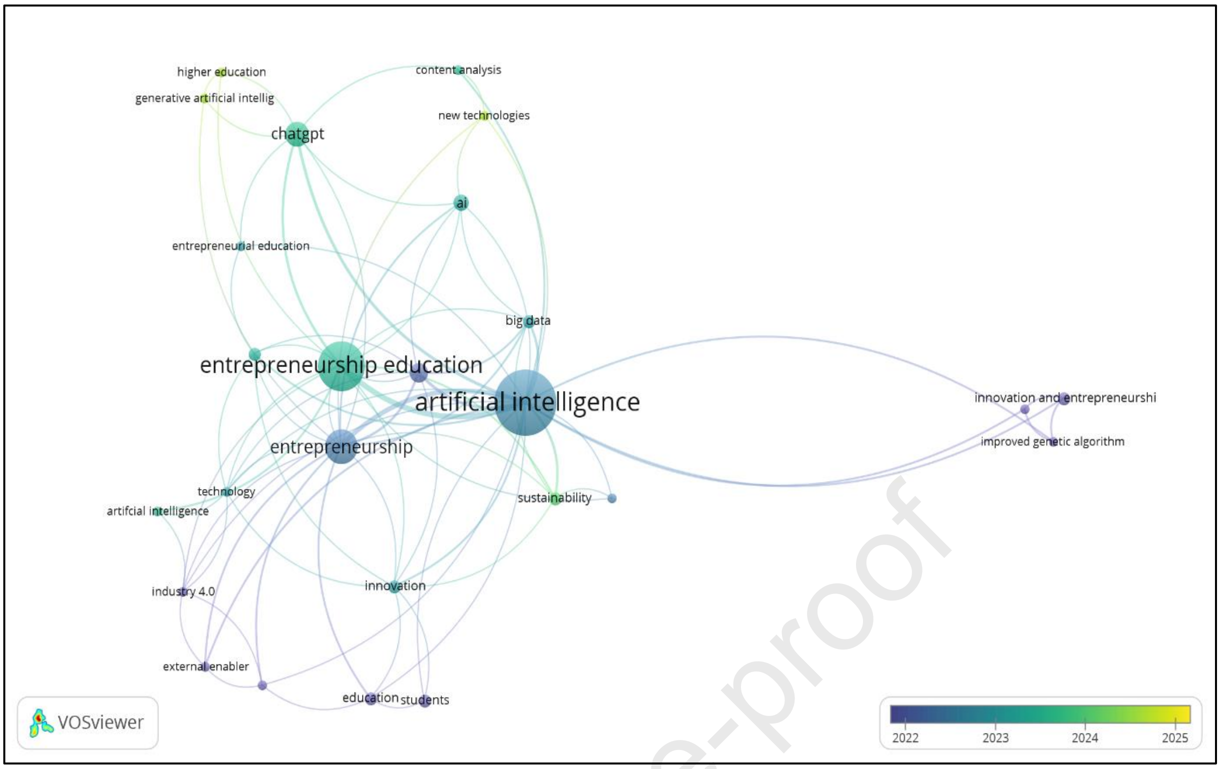

Figure. 7. Overlay visualization co-assurance (Keywords).

Further analysis of the temporal evolution of keywords (Figure 7) provides insights into the development trajectory of AI research in EE. The research time frame spans from 2019 to 2025, which can be categorized into three distinct phases: the exploratory phase (before 2022), the development phase (2022-2024), and the deepening phase (2024-present). Different colors denote different periods in the visual representation: purple signifies earlier research, blue-green represents mid-stage development, and yellow highlights the most recent trends. During the exploratory phase (before 2022), research primarily focused on the potential of AI as an external enabler in innovation and EE. Studies explored the role of AI in technology-driven Industry 4.0 and the optimization of entrepreneurship learning. Key terms such as “improved genetic algorithm”, “opportunity”, “education”, and “students” indicate that early studies centered on AI’s initial integration into the entrepreneurial ecosystem, particularly in how AI-driven algorithms could optimize entrepreneurial learning environments and improve educational effectiveness. However, this phase remained largely conceptual, with limited empirical research on AI’s direct impact on EE. During the development phase (2022-2024), research shifted from theoretical discussions to data-driven empirical analysis, emphasizing the practical applications of AI in EE and the development of a more structured entrepreneurial ecosystem. Frequently occurring keywords such as “artificial intelligence”, “entrepreneurship education”, “big data”, “sustainability”, and “innovation” reflect the growing interest in personalized learning pathways, data analytics in EE, and the formation of sustainable entrepreneurship models. Studies during this period expanded beyond AI’s technical potential, instead focusing on measuring its impact on students’ entrepreneurial capabilities, innovation skills, and improvements to the educational system.

Notably, 23 papers, nearly half of the analyzed studies, were published during this period, highlighting the rapid surge in research interest and scholarly engagement with AI-enabled EE. In the deepening phase (2024-present), research has become increasingly focused on the applications of GAI in EE, driving the evolution of personalized learning and AI-powered entrepreneurial training models. Core keywords such as “ChatGPT”, “generative artificial intelligence”, and “higher education” suggest that researchers are placing a greater emphasis on AI’s integration into higher education, particularly in areas like entrepreneurship course design, pedagogical innovation, and AI-driven knowledge generation. Additionally, the emergence of “new technologies” as a keyword signals a trend toward integrating AI with other cutting-edge technologies, potentially broadening the scope of AI-supported EE. As Jeremiah (2025) highlighted in his study on the Human-AI Dyad concept, AI is reshaping entrepreneurial identity and business practices, while transhuman synergy further contributes to the ongoing digitalization and AI-supported evolution of EE. From a broader perspective, Figure 6 visually illustrates the research trajectory of AI in EE, demonstrating a gradual shift from early theoretical explorations to practical applications and technological integration.

This evolution reflects the expanding depth and breadth of research in this domain. Over time, the focus of studies has shifted from conceptual discussions on AI-enabled EE to data-driven optimization strategies, ultimately advancing toward the development of personalized learning and AI-powered intelligent entrepreneurial ecosystems. Simultaneously, advancements in AI technology have also influenced research methodologies, transitioning from the construction of theoretical frameworks to empirical analyses and applied technology research, signaling a shift from exploratory studies to practical implementations. The emergence of GAI reflects a growing trend toward personalization and intelligent systems in EE. It may contribute to the ongoing digitalization of entrepreneurial learning and influence both pedagogical practices and broader ecosystem development.

3.5. Thematic synthesis findings

As research on AI applications in EE begins to shift from theoretical exploration toward more empirical investigations, scholars have increasingly examined ways to improve EE models, support entrepreneurial cognition and decision-making, and contribute to the development of entrepreneurial ecosystems (Chen et al., 2024; Giuggioli & Pellegrini, 2023; Roundy & Asllani, 2024). Based on the keyword co-occurrence analysis presented earlier, researchers' focus on AI in EE can be categorized into three primary areas: (1) how AI optimizes EE and learning, with an emphasis on data-driven personalized learning and AI-enabled entrepreneurial simulation training; (2) how AI shapes entrepreneurs' cognitive abilities, entrepreneurial intention, self-efficacy, and business decision-making; and (3) AI's enabling role in the entrepreneurial ecosystem, including its applications in business incubation, intelligent investment and financing, and policy optimization to improve the practicality of EE and improve resource allocation efficiency. This section integrates existing literature to discuss these three research directions, analyzing key findings, methodological trends, and potential avenues for future research. Table 3 provides a structured framework summarizing AI applications in EE and ecosystem development, outlining key research areas, application scenarios, and technological practices. This section integrates existing literature to discuss these three research directions, analyzing key findings, methodological trends, and potential avenues for future research.

Table. 3. Framework of AI applications in entrepreneurship education and ecosystem development.

Core theme	Research focus	Application scenarios	Key technologies & practices	Representative literature
AI in entrepreneurship education and ecosystem development	AI-supported entrepreneurship education & learning	Adaptive & personalized learning	Adaptive learning Real-time feedback Intelligent tutoring	Obschonka and Audretsch (2020); Xu et al. (2022); Zhu and Zhang (2022); Bell and Bell (2023); Winkler et al. (2023); Fox et al. (2024); Liang and Bai (2024)
		Entrepreneurship simulation and practical training	Entrepreneurship simulation and virtual labs Business analysis Entrepreneurial team management & incubation support	Mavlutova et al. (2020); Nowak (2020); Chen et al. (2022); Liang and Bai (2024); Fox et al. (2024); Bickley et al. (2025)
	AI-driven entrepreneurial decision-making and behavior	Market insight & cognitive enhancement	Big data analytics Predictive AI for market insights	Tkachenko et al. (2019); Obschonka and Audretsch (2020); Giuggioli and Pellegrini (2023); Jeremiah (2025)
		Entrepreneurial intention & self-efficacy	Problem-based learning Intelligent entrepreneurial mentorship systems	Obschonka and Audretsch (2020); Zhu and Zhang (2022); Xu et al. (2022); Zhu and Zhang (2022); Torres Ortega et al. (2025)
		Strategic decision-making & risk management	Scenario simulation Risk analysis & mitigation	Chen et al. (2022); Dabbous and Boustani (2023); Giuggioli and Pellegrini (2023); Jeremiah (2025)
	AI-enabled entrepreneurial ecosystem development	Venture capital management	Investment analysis Entrepreneurial project valuation	Jing and Jan (2022); Davidsson and Sufyan (2023); Roundy and Asllani (2024)

	Entrepreneurship incubation efficiency	Incubation management Automated resource allocation	Chalmers et al. (2021); Bell and Bell (2023); Roundy and Asllani (2024); Thottoli et al. (2024)
	Entrepreneurship policy making	Policy simulation Entrepreneurial support program optimization	Townsend and Hunt (2019); Liang and Bai (2024); Weng et al. (2025)

3.5.1. AI-Driven Personalized Learning and Entrepreneurship Simulation

In recent years, the application of AI in EE has expanded considerably, with researchers increasingly examining its potential to support personalized learning pathways and to enable entrepreneurship simulation and practice, which may contribute to improved adaptability and practical orientation in EE (Chen & Aljawarneh, 2022; Jing & Jan, 2022; Voronov et al., 2023; Xu & Sun, 2022; Xu et al., 2022; Zhang et al., 2022). Existing studies primarily investigate how AI supports personalized learning through big data analytics, intelligent recommendation systems, and dynamic curriculum adjustments, as well as how AI-driven entrepreneurship simulation facilitates entrepreneurs' practical skills and business decision-making capabilities (Table 3) (Chen & Aljawarneh, 2022; Nowak, 2020).

Personalized learning is a core application of AI in EE. Unlike traditional standardized teaching models, AI-driven personalized learning leverages big data analytics, machine learning algorithms, and intelligent recommendation systems to dynamically adjust the course content to match different learners' cognitive levels and entrepreneurial needs (Fox et al., 2024; Mavlutova et al., 2020; Nowak, 2020). GAI has been widely used in entrepreneurial case analysis, business model innovation, and business plan writing, providing learners with real-time intelligent feedback and enhancing the interactivity of entrepreneurship courses (Bell & Bell, 2023; Liang & Bai, 2024; Short & Short, 2023). Furthermore, AI-powered personalized learning can automatically adjust teaching strategies based on learner feedback, delivering tailored EE content. Although AI's role in personalized learning has become a focal point in theoretical research, empirical studies on its impact on entrepreneurial learning outcomes remain limited, particularly in systematic quantitative evaluations (Fox et al., 2024; Giuggioli & Pellegrini, 2023; Truong et al., 2023). Researchers have increasingly employed experimental studies, surveys, and quantitative analyses in recent years to assess AI's effectiveness in optimizing personalized learning pathways in EE (Zhou et al., 2024; Zhu & Zhang, 2022). Moreover, scholars are exploring how AI-driven big data analytics, intelligent recommendation systems, and dynamic curriculum adjustments can further support adaptability and learning efficiency in EE (Kinnula et al., 2024; Vecchiarini & Somià, 2023).

Beyond personalized learning pathways, AI applications in entrepreneurship simulation and practical training have gained significant attention. Traditional entrepreneurship simulation training relies on case studies, business competitions, and market experiments. However, these methods have inherent limitations, such as the inability to provide real-time market feedback, difficulties in simulating complex business environments, and challenges in meeting personalized entrepreneurial training needs (Lackéus, 2020). Integrating AI technologies has contributed to making entrepreneurship simulation training more precise, intelligent, and interactive. AI-driven entrepreneurship training reshapes conventional EE paradigms, particularly in market forecasting, business plan evaluation, and entrepreneurial risk management (Fox et al., 2024; Liang & Bai, 2024; Mavlutova et al., 2020; Nowak, 2020). Scholars are currently exploring how AI, combined with virtual entrepreneurship environments and AR/VR technologies, enables students to engage in business decision-making, supply chain management, and financial investment simulations in highly immersive market environments. AI provides real-time data feedback to optimize entrepreneurial decision-making and strategy adjustments (Li et al., 2022; Liang & Bai, 2024; Mavlutova et al., 2020; Nowak, 2020). Additionally, AI-driven business plan analysis can automatically evaluate business plans, market analysis reports, and financial forecasts, offering targeted improvement suggestions (Shepherd & Majchrzak, 2022; Winkler et al., 2023).

AI also plays a crucial role in market trend forecasting by analyzing market data, industry dynamics, and consumer behavior to support entrepreneurs in making more informed business decisions (Mavlutova et al., 2020; Tkachenko et al., 2019). Beyond business decision-making and market analysis, AI is increasingly utilized in entrepreneurial team management and incubation support. AI assists students in optimizing team collaboration based on individual traits and skills, improving the compatibility of entrepreneurial projects. It also improves startup incubation by analyzing market demand and failure cases to provide personalized support, ultimately increasing entrepreneurial success rates (Roundy & Asllani, 2024; Thottoli et al., 2024). While research on AI applications in EE continues to grow, current studies primarily focus on personalized learning and entrepreneurship simulation. However, systematic empirical analyses are still lacking in areas such as AI's long-term impact on entrepreneurial learning outcomes, practical implementation, and entrepreneurial success rates. Future research should investigate the long-term effects of AI-enabled EE and integrate multi-dimensional data analysis to reveal AI's role in EE comprehensively.

3.5.2. AI-Driven Entrepreneurial Cognition, Intention, and Decision-Making

AI has optimized EE models and profoundly influenced entrepreneurs' cognition, intentions, and decision-making behaviors (Shepherd & Majchrzak, 2022; Tkachenko et al., 2019). Existing studies primarily focus on how AI influences entrepreneurs' market insights, entrepreneurial intention (EI), ESE, and data-driven decision-making capabilities (Dabbous & Boustani, 2023; Shepherd & Majchrzak, 2022; Townsend & Hunt, 2019). Through large-scale data analysis, pattern recognition, and intelligent forecasting, AI provides entrepreneurs with precise business scenario simulations and decision-making support, enhancing their market adaptability, reducing cognitive biases, and improving commercial judgment (Table 3) (Bickley et al., 2025; Giuggioli & Pellegrini, 2023; Truong et al., 2023).

Studies indicate that AI is crucial in market analysis, information processing optimization, and improving innovation cognition (Darnell & Gopalkrishnan, 2024; Tkachenko et al., 2019). Traditional entrepreneurial decision-making relies heavily on personal experience and limited data analysis capabilities. In contrast, AI, leveraging deep learning and data mining, can analyze industry trends, consumer behaviors, and competitive dynamics in real-time, providing data-driven insights (Obschonka & Audretsch, 2020; Shepherd & Majchrzak, 2022; Townsend & Hunt, 2019). AI-powered business intelligence (BI) systems have been widely adopted for market forecasting and business scenario analysis, enabling entrepreneurs to develop a more comprehensive understanding of market environments and make data-backed decisions (Giuggioli & Pellegrini, 2023; Thottoli et al., 2024; Zhu & Zhang, 2022). Additionally, AI-driven cognitive enhancement systems assist entrepreneurs in refining their business models, improving adaptability, and increasing the precision of opportunity recognition and business model innovation (Giuggioli & Pellegrini, 2023; Shepherd & Majchrzak, 2022; Voronov et al., 2023).

AI's application in EE has the potential to support the learning experience and may influence EI and ESE. Existing studies suggest that AI-powered personalized learning systems and intelligent recommendation platforms can support the development of learners' entrepreneurial confidence, which in turn may help them approach business planning and decision-making with greater clarity and initiative (Dabbous & Boustani, 2023; T. Nuseir et al., 2020; Zhu & Zhang, 2022). Recent SEM research has further validated AI's role in shaping EI, particularly in strengthening perceived behavioral control (PBC) (Dabbous & Boustani, 2023; Lesinskis et al., 2023; T. Nuseir et al., 2020). For instance, Dabbous and Boustani (2023) found that when integrated into EE, AI-generated performance expectations effectively support learners' PBC, reinforcing their entrepreneurial intentions. Zhu and Zhang (2022) further highlighted that PBL models powered by AI-driven personalized recommendations improve entrepreneurial education experiences, making learners more confident in entrepreneurial cognition, decision-making, and market analysis. Additionally, AI-driven EE systems help entrepreneurs develop market analysis skills and problem-solving abilities, thereby strengthening their ESE and increasing their confidence in business plan development and implementation (Torres Ortega et al., 2025; Zhu & Zhang, 2022). AI-powered entrepreneurial simulation training has also been found to positively impact ESE. For example, AI-driven PBL systems have supported students' entrepreneurial capabilities, including teamwork, market analysis, and business plan optimization (Zhu & Zhang, 2022). Moreover, AI-integrated business simulation games and market trend analysis assist entrepreneurs in identifying key variables during the decision-making process, improving opportunity recognition, and refining strategic thinking (Chen et al., 2022; Torres Ortega et al., 2025).

Beyond its potential to support cognitive development, AI may also contribute to improving data-informed decision-making processes in EE (Bell & Bell, 2023; Chen et al., 2022; Jeremiah, 2025). AI-powered market forecasting models, leveraging machine learning and big data analytics, improve the accuracy of market trend predictions, providing entrepreneurs with intelligent decision support (Bell & Bell, 2023; Giuggioli & Pellegrini, 2023; Mavlutova et al., 2020; Shepherd & Majchrzak, 2022). Studies have shown that AI-driven market analysis can extract deep industry insights, reducing uncertainties related to market entry, enabling entrepreneurs to plan business activities scientifically, and mitigating risks (Jeremiah, 2025; Truong et al., 2023). AI-powered entrepreneurial simulation training has also been widely adopted in EE. For example, AI-driven business simulation games provide real-time data feedback, enabling learners to quickly adapt to market changes and refine their response strategies (Chen et al., 2022; Thanasi-Boçe & Hoxha, 2024; Voronov et al., 2023). Additionally, AI is an intelligent decision-support tool in business plan formulation, market research, and risk assessment (Chen & Aljawarneh, 2022; Jeremiah, 2025; Townsend & Hunt, 2019). The cognitive neuro-fuzzy model, integrating fuzzy logic and neural networks, has been widely applied in business decision-making, improving entrepreneurs' precision in financial forecasting, resource allocation, and business model adjustments (Table 3) (Jeremiah, 2025; Tkachenko et al., 2019; Townsend & Hunt, 2019).

However, despite AI's strengths in data analysis and market prediction, research also indicates that human judgment, innovation, and strategic planning remain irreplaceable (Jeremiah, 2025; Townsend & Hunt, 2019). Current studies explore how AI-enabled entrepreneurial decision-making systems can balance data analytics and human intuition, aiming to improve entrepreneurs' comprehensive decision-making abilities. AI in EE supports entrepreneurs' cognitive abilities, strengthens their EI and ESE, and improves their data-driven decision-making skills. However, current research predominantly focuses on short-term decision-making optimization, with limited discussions on AI's role in shaping long-term entrepreneurial thinking. Future research should further explore AI's long-term impact on EE and investigate human-AI symbiosis to develop a balanced model integrating AI-driven analytics with human intuition, thereby enhancing entrepreneurs' holistic decision-making abilities.

3.5.3. AI-Enabled Optimization of the Entrepreneurial Ecosystem

The application of AI in the entrepreneurial ecosystem supports the intelligent development of EE by optimizing incubation mechanisms, enhancing investment decision-making, and facilitating policy refinement. These advancements enable entrepreneurs to grow in a data-driven environment (Table 3) (Liang & Bai, 2024; Roundy & Asllani, 2024; Thottoli et al., 2024). In university-based EE, AI-driven incubation models improve resource allocation efficiency and provide intelligent support systems for entrepreneurs (Roundy & Asllani, 2024; Thottoli et al., 2024). Traditional incubators mainly rely on manual management and experience-based decision-making. In contrast, AI integrates big data analytics and intelligent matching algorithms to accurately identify entrepreneurs' needs and dynamically connect them with mentors, investors, partners, and industry resources (Giuggioli & Pellegrini, 2023; Obschonka & Audretsch, 2020; Roundy & Asllani, 2024). Furthermore, AI-driven incubation management systems can track the growth trajectories of entrepreneurial teams in real-time, providing tailored feedback that integrates actual market conditions into EE curricula. This allows students to gain practical business experience in simulated incubation environments (Bell & Bell, 2023; Jing & Jan, 2022; Kleine et al., 2020). Studies suggest that such AI-driven incubation models increase startup success rates and improve students' ability to navigate market challenges (Bell & Bell, 2023; Kang, 2022; Thottoli et al., 2024).

Integrating AI into investment and financing management has enabled universities to incorporate intelligent investment simulations into EE. This enables students to comprehend investment logic and acquire essential financial skills (Chen et al., 2022; Mavlutova et al., 2020; Roundy & Asllani, 2024). AI-powered investment management systems leverage machine learning algorithms, market trend analysis, and entrepreneurial background assessments to predict the potential market value of startups and recommend optimal financing strategies (Giuggioli & Pellegrini, 2023; Jing & Jan, 2022; Thanasi-Boçe & Hoxha, 2024; Thottoli et al., 2024). Additionally, AI-driven investment solutions improve the accuracy of data analytics and optimize capital allocation, increasing investment success rates (Jing & Jan, 2022; Roundy & Asllani, 2024). Universities are integrating AI-supported investment tools to provide students with realistic investment environments to assess business plans, forecast financial risks, and develop financing strategies (Thanasi-Boçe & Hoxha, 2024; Thottoli et al., 2024).

The use of AI in policy assessment and ecosystem optimization has also gained momentum. Governments and entrepreneurship support organizations employ AI for market monitoring, policy evaluation, and funding allocation to facilitate policy precision and create a more favorable entrepreneurial environment (Lauterbach, 2019; Liang & Bai, 2024; Winkler et al., 2023). AI-powered prominent data analytics help policymakers assess the impact of entrepreneurship policies and simulate different scenarios to optimize government support programs (Bickley et al., 2025; Chen et al., 2022; Long & He, 2023). Additionally, AI-driven policy simulation tools have been integrated into university EE, helping students understand the influence of government policies on business decision-making and how to leverage policy incentives for startup development (Bharathi et al., 2024; Liang & Bai, 2024). The incorporation of such AI-driven tools not only improves entrepreneurs' adaptability to policy environments and provides data support for future policy formulation (Table 3) (Long & He, 2023). Despite AI's potential in entrepreneurial incubation, investment optimization, and policy assessment, its widespread application still faces challenges related to data security, algorithmic bias, and ethical fairness (Jeremiah, 2025; Weng et al., 2025). Future research should focus on the deep integration of AI in incubation management, investment decision-making, and policy development to improve resource efficiency, optimize funding allocation, and ensure policy fairness. Additionally, exploring human-AI symbiosis is crucial to balancing AI's analytical capabilities with entrepreneurial creativity, fostering a more intelligent and sustainable entrepreneurial ecosystem. Moreover, further studies are needed to assess AI's adaptability in various market environments and its long-term impact on EE, ensuring its sustainable role in fostering innovation-driven entrepreneurial ecosystems.

3.6. AI-driven Elements in Entrepreneurship Education

The application of AI in EE is contributing to the evolution of traditional teaching and training models by encouraging more intelligent, data-driven, and personalized approaches. Researchers focus on the role of AI in personalized learning, market forecasting, and business decision-making. They also explore how it improves entrepreneurial capability development and practical application through content generation, intelligent learning systems, collaboration, and strategic decision-making optimization. Compared to traditional EE, which relies on static materials and experience-based guidance, AI-powered models are more dynamic, adaptive, and practice-oriented, enabling entrepreneurs to engage in continuous learning and optimization based on data-driven insights. This section identifies the key impact dimensions of AI in EE. It discusses its applications in content creation, learning models, entrepreneurial collaboration, and decision support, analyzing how AI shapes the entrepreneurial education ecosystem while providing directions for future research.

3.6.1. AI-Driven Content Generation in Entrepreneurship Education

The integration of AI into content creation for EE is contributing to the evolution of traditional teaching models by enabling the development of more intelligent, dynamic, and market-responsive learning resources (Bell & Bell, 2023; Marchena Sekli & Portuguez-Castro, 2025; Short & Short, 2023). Unlike conventional entrepreneurship courses that rely on static textbooks, AI leverages GAI, natural language processing (NLP), and big data analytics to automatically create, refine, and update educational content in real-time, thereby improving the accessibility and practical relevance of EE (Thottoli et al., 2024; Winkler et al., 2023). The impact of AI in content creation for EE is primarily reflected in three key dimensions: real-time content updates, personalized recommendations, and interactive learning experiences. AI-powered content updates ensure that EE materials remain aligned with industry trends. GAI can automatically generate business case studies, market research reports, business plans, and financial forecasts while integrating market data to ensure content relevance and timeliness (Bell & Bell, 2023; Darnell & Gopalkrishnan, 2024; Ravichandran et al., 2024). For example, AI can dynamically create entrepreneurship simulation cases based on changes in the market environment, allowing students to study emerging business challenges rather than relying on outdated case studies (Chen et al., 2022; Liang & Bai, 2024).

AI-driven personalized content recommendations support the precision and efficiency of EE. AI adapts course structures through learner profiling and recommends the most relevant entrepreneurial knowledge and practice cases based on learners' cognitive levels, industry backgrounds, and market needs (Fox et al., 2024; Xu & Sun, 2022). For instance, in entrepreneurship training programs, AI can generate customized business model analyses and competitive strategy reports, making learning experiences more personalized and practice-oriented (Darnell & Gopalkrishnan, 2024; Mavlutova et al., 2020). Beyond static text-based materials, AI-generated interactive learning experiences improve EE through virtual entrepreneurship cases, business scenario simulations, and dynamic market conditions modeling (Chen et al., 2022; Li et al., 2022). For example, AI-powered entrepreneurship simulation systems can adjust market competition dynamics in real-time, enabling learners to engage in an AI-driven business ecosystem and develop market adaptability (Obschonka & Audretsch, 2020; Roundy & Asllani, 2024). Overall, AI facilitates the optimization of EE content through real-time updates, personalized recommendations, and interactive learning experiences, shifting EE toward a more data-driven and flexible learning model. However, the long-term impact of AI in EE still requires further empirical validation, particularly regarding its influence on learning effectiveness. Future research could further explore advancements in AI-driven content generation and assess its adaptability across different educational contexts to ensure that EE resources remain responsive to market dynamics.

3.6.2. AI-Driven Adaptive Learning in Entrepreneurship Education

AI is contributing to the evolution of learning models in EE by enabling a gradual move from traditional linear teaching toward more data-driven, experiential, and adaptive learning approaches. This shift enables entrepreneurs to acquire entrepreneurial skills in a personalized, practice-oriented, and dynamically adjustable environment (Jia et al., 2022; Kang, 2022). Unlike traditional education models that rely on instructor-led teaching and fixed curricula, AI integrates machine learning, GAI, and big data analytics to construct personalized learning pathways, making EE more intelligent and efficient (Chen & Aljawarneh, 2022; Obschonka & Audretsch, 2020; Thanasi-Boçe & Hoxha, 2024). AI-powered learning models primarily contribute to three key areas: personalized learning pathways, experiential entrepreneurial learning, and adaptive learning systems. First, AI-powered personalized learning pathways support the precision of EE by tailoring learning content to individual needs. AI-driven learner profiling and predictive learning models dynamically adjust course content, recommending the most relevant entrepreneurial knowledge and case studies to ensure more targeted learning pathways (Gandoul et al.; Jing & Jan, 2022). This mechanism improves the efficiency of knowledge acquisition and allows EE to cater to learners' diverse backgrounds and learning requirements. Second, AI facilitates experiential entrepreneurial learning, reinforcing students' business practice capabilities. By integrating entrepreneurial simulation, AR, and VR, AI creates highly immersive business ecosystems that enable learners to develop skills in market analysis, business decision-making, and team management (Chen et al., 2022; Li et al., 2022).

For instance, AI-driven dynamic market environments adjust competitive conditions based on learners' decision feedback, providing a near-realistic business simulation experience that improves students' commercial judgment (Liang & Bai, 2024; Nowak, 2020). Lastly, AI-powered adaptive learning systems make EE more intelligent and efficient. AI utilizes adaptive learning technologies and data analytics platforms to adjust learning strategies based on learners' performance and market needs, improving innovation capabilities and business decision-making precision (Xu et al., 2022; Zhu & Zhang, 2022). For example, AI can automatically analyze learners' behavioral data, identify weaknesses in business model design, marketing, or financial management, and recommend targeted learning resources (Giuggioli & Pellegrini, 2023; Xu & Sun, 2022). This ensures that entrepreneurs continuously refine their knowledge framework and quickly adapt to market challenges in the entrepreneurial process. AI-driven learning models facilitate EE by providing personalized recommendations, practice-oriented training, and dynamic adaptation, optimizing the learning experience and facilitating knowledge translation into entrepreneurial practice. These AI-powered approaches improve the flexibility and precision of EE while strengthening students' decision-making abilities in complex market environments. However, existing research primarily examines AI's short-term impact on learning performance, with limited systematic analysis of its long-term effects on entrepreneurial success. Further studies should investigate how AI-driven personalized learning pathways influence sustained entrepreneurial outcomes and explore the collaborative role of AI within EE ecosystems to improve the sustainability and market competitiveness of entrepreneurial learning.

3.6.3. AI-Enabled Interactive Learning & Entrepreneurial Collaboration

AI-driven interaction and collaboration models in EE optimize mentor guidance, investment matching, and team collaboration, enabling entrepreneurs to grow in a more intelligent, efficient, and data-driven environment (Liang & Bai, 2024; Obschonka & Audretsch, 2020). Unlike traditional face-to-face mentoring, fixed teaching models, and subjective investment decisions, AI supports entrepreneurial education through three key aspects: intelligent mentoring systems, AI-powered investment matching, and entrepreneurial team collaboration, improving interaction by making it more precise, flexible, and cooperative.

First, AI-powered intelligent mentoring systems improve personalized guidance in EE. Traditional mentoring models are limited by geographical, time, and resource constraints. In contrast, leveraging NLP and GAI, AI provides 24/7 intelligent, entrepreneurial consultation, making mentor-learner interactions more flexible (Liang & Bai, 2024; Thottoli et al., 2024). Moreover, AI can intelligently match the most suitable mentors based on entrepreneurs' industry background, business model, and development stage, offering data-driven entrepreneurial advice to ensure learners receive more precise and practical guidance (Chen & Aljawarneh, 2022; Voronov et al., 2023). This mechanism expands the accessibility of entrepreneurial mentorship while improving the accuracy of personalized coaching, promoting the scalability and intelligence of EE. Second, AI facilitates intelligent investment matching, optimizing the funding process for entrepreneurs. Traditional entrepreneurial financing relies on offline events, investors' subjective judgment, and experience-based assessments, whereas AI leverages big data analytics and machine learning to streamline the investment process, enabling entrepreneurs to connect more accurately with potential investors (Rossi, 2023; Roundy & Asllani, 2024). AI evaluates startups' market potential, team composition, and financial health, automatically matching them with the most suitable funding channels and providing data-driven recommendations to optimize financing strategies (Makse & Zava, 2025; Maurer et al., 2024). Furthermore, AI can analyze historical investment data, industry trends, and market forecasts to assist investment institutions in evaluating startups, enhancing investment efficiency while mitigating risks.

Ultimately, AI-powered collaboration among entrepreneurial teams enhances project execution efficiency. AI integrates intelligent task management, team behavior analysis, and remote collaboration platforms, enabling cross-regional and interdisciplinary cooperation (Hammoda, 2024; Kleine et al., 2020). AI optimizes task allocation based on team members' skills, project requirements, and work styles, predicts potential collaboration bottlenecks, and provides data-driven optimization strategies to facilitate team coordination (Chen et al., 2022; Zhu & Zhang, 2022). Additionally, AI monitors real-time team dynamics, analyzes collaboration patterns, and provides personalized feedback, improving communication efficiency and decision-making in entrepreneurial teams. AI optimizes the interaction models of EE by enhancing mentor guidance, intelligent investment matching, and entrepreneurial team collaboration, making learning interactions more precise, efficient, and intelligent.

These AI-enabled interactive models reduce resource barriers in EE while improving entrepreneurs' practical capabilities, decision-making efficiency, and team collaboration skills. However, current research mainly focuses on AI's optimization of individual interaction components, with limited studies on its long-term impact on entrepreneurial growth and team stability. Future studies should explore AI's role in interdisciplinary, cross-regional EE and its integration into entrepreneurial ecosystems to ensure the sustainability of AI-driven interaction models in EE.

3.6.4. AI-Augmented Strategic Decision-Making in Entrepreneurship Education

The role of AI in decision-making support within EE is shifting from traditional experience-based judgment models to data-driven, predictive analytics and intelligent optimization approaches. By facilitating business plan evaluation, market forecasting, and personalized decision optimization, AI-powered systems provide entrepreneurs with data-driven decision-making mechanisms, helping them formulate more forward-looking strategies in complex business environments (Chen et al., 2024; Mavlutova et al., 2020; Winkler et al., 2023). Unlike traditional models that rely on subjective experience and fixed analytical frameworks, AI improves entrepreneurs' strategic thinking and adaptability in uncertain environments through three key components: intelligent business plan evaluation, market forecasting analysis, and personalized decision optimization.

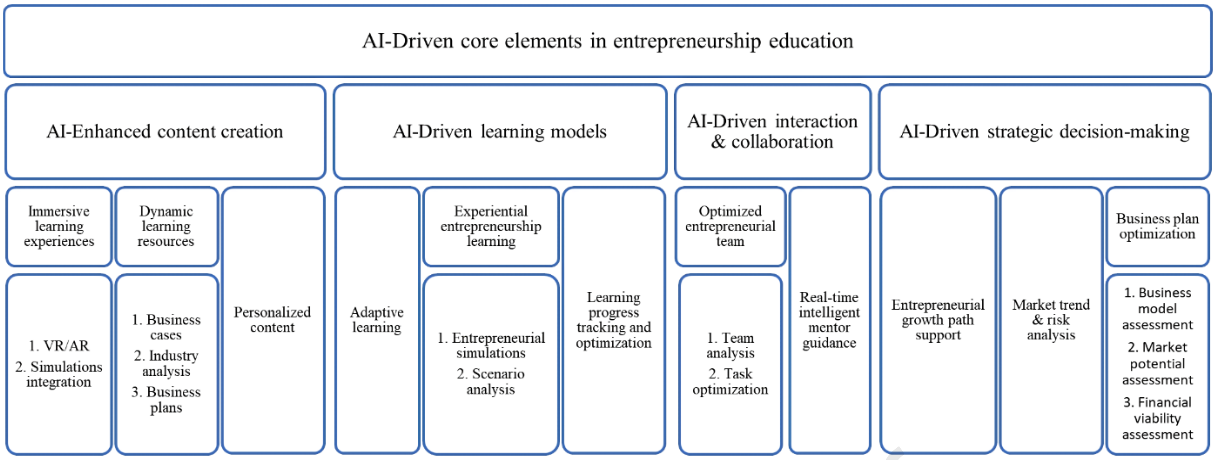

Figure 8. AI-Driven core elements in entrepreneurship education.

First, AI-powered intelligent business plan evaluation improves the scientific rigor and feasibility of entrepreneurial decision-making. Traditional business plan evaluation often depends on entrepreneurs' personal experiences or subjective judgments from mentors. In contrast, leveraging NLP and machine learning, AI can assess the structure, market potential, and financial feasibility of business plans, providing data-driven optimization recommendations (Bell & Bell, 2023; Thottoli et al., 2024). For example, AI can automatically evaluate the viability of business models, identify potential risks, and recommend strategy adjustments based on historical data, allowing entrepreneurs to refine their business plans with greater precision (Hajipour et al., 2023; Thottoli et al., 2024; Townsend & Hunt, 2019). Second, AI-powered market forecasting analysis enables entrepreneurs to formulate more forward-looking business strategies in uncertain environments. AI integrates scenario modeling, industry trend forecasting, and competitive intelligence analysis to simulate different market conditions and provide data-supported business decision-making strategies (Chen et al., 2022; Giuggioli & Pellegrini, 2023; Mavlutova et al., 2020).

For instance, AI can analyze real-time industry data to track shifts in market demand and recommend optimal market entry strategies, helping entrepreneurs develop adaptive market response plans (Obschonka & Audretsch, 2020; Patil, 2024). Additionally, AI-powered personalized decision optimization combines cognitive computing, risk prediction modeling, and long-term growth path analysis to offer entrepreneurs personalized strategic recommendations (Jing & Jan, 2022; Obschonka & Audretsch, 2020). AI can track entrepreneurs' learning trajectories by integrating entrepreneurial skills assessments and personalized learning paths, providing adaptive decision-making support (Olatunde-Aiyedun et al., 2024; Xu & Sun, 2022). For example, AI can assess an entrepreneur's project progress, market feedback, and financing data to predict business development paths and recommend optimized growth strategies, ensuring access to targeted resources and learning opportunities at different entrepreneurial stages (Fox et al., 2024; Obschonka & Audretsch, 2020).

In summary, AI-driven strategic decision-making in EE is primarily reflected in three core dimensions: intelligent business plan evaluation, market forecasting analysis, and personalized decision optimization. These AI-powered tools support entrepreneurs' business decision-making capabilities in complex market environments and promote EE's transition toward data-driven evaluation, personalized assessment, and long-term growth support. However, current research focuses primarily on AI's role in short-term strategy optimization, with limited systematic analysis of its impact on entrepreneurs' long-term development pathways. Future research could further explore how AI can leverage large-scale entrepreneurial data to optimize entrepreneurial growth trajectories and assess its applicability across different market environments to ensure the sustainable integration of AI into EE. Based on the key findings in this section, the AI-driven elements in EE can be systematically categorized into four fundamental dimensions: content creation, learning models, interaction & collaboration, and strategic decision-making. These dimensions encapsulate the core mechanisms AI improves EE, enabling more adaptive learning experiences, intelligent collaboration, and data-driven decision-making. Figure 8 summarizes these AI-powered elements and their applications in EE to provide a structured overview.

4. Discussion

This section discusses the role of GAI in EE, systematically analyzing its impact on optimizing the learning process, supporting entrepreneurial decisions, and enabling the entrepreneurial ecosystem. Based on the findings of Section 3, this section further explores the theoretical significance and practical implications of GAI in EE while also examining its limitations and proposing future research directions to advance the integration and optimization of GAI in this field.

4.1. Comprehensive Research Findings

This study systematically reviewed 50 relevant papers and identified three core dimensions of GAI enhancing EE: teaching and learning, entrepreneurial capabilities, and the entrepreneurial ecosystem. This classification is based on AI applications at different stages of EE, covering the transition from individual learning to entrepreneurial practice and the broader evolution of the entrepreneurial ecosystem. This structured classification helps provide a comprehensive understanding of AI's multidimensional impact on EE and serves as a framework for further theoretical analysis and practical exploration. The following sections examine AI's role in these three dimensions. AI-powered learning models in EE are increasingly shifting from traditional static courses toward more personalized, immersive, and data-driven approaches, which may contribute to improved student learning experiences and knowledge acquisition. For instance, AI-driven entrepreneurial simulation systems enable students to practice entrepreneurial decision-making in a low-risk environment, providing instant feedback and improving their ability to handle complex business scenarios (Chen et al., 2022; Mavlutova et al., 2020; Nowak, 2020). Additionally, intelligent question-answering tools based on LLMs remove traditional classroom constraints related to time and instructor availability, making learning more autonomous and flexible (Liang & Bai, 2024; Torres Ortega et al., 2025). Empirical studies indicate that integrating AI-powered tools into EE courses supports students' understanding and optimization of business plans, while also improving their adaptability to market dynamics (Fox et al., 2024; Hammoda, 2024; Jing & Jan, 2022; Voronov et al., 2023). These studies collectively demonstrate that GAI facilitates EE toward greater personalization, interactivity, and intelligence, while supporting teaching quality and learning outcomes.

AI-powered EE may help refine teaching models and has been associated with improvements in students' ESE and EI. (Torres Ortega et al., 2025; Xu et al., 2022; Zhu & Zhang, 2022). For example, AI-powered business plan evaluation systems provide intelligent feedback, helping students better understand critical aspects of business model development and market analysis, thereby increasing their entrepreneurial confidence (Lesinskis et al., 2023; T. Nuseir et al., 2020). Furthermore, AI-supported data-driven market analysis and AI-powered risk assessment enable students to make more rational business decisions based on comprehensive information, improving their adaptability to market changes (Obschonka & Audretsch, 2020; Townsend & Hunt, 2019). Additional research reflects that incorporating AI into entrepreneurship training improves market forecasting accuracy for startup teams and supports their ability to integrate resources effectively (Kang, 2022; Xu & Sun, 2022). Beyond individual skill enhancement, AI also optimizes entrepreneurial team collaboration and innovation capacity. For instance, AI-driven creativity generation systems facilitate idea generation among team members, promote interdisciplinary collaboration, improve innovation performance, and streamline teamwork processes (Kinnula et al., 2024; Somia & Vecchiarini, 2024). These findings suggest that GAI is becoming an increasingly intelligent assistant in EE, enhancing students' entrepreneurial competencies and providing them with practical entrepreneurial experience before entering the workforce, thereby laying a solid foundation for future entrepreneurial endeavors.

AI's applications in the entrepreneurial ecosystem contribute to the optimization of university-based entrepreneurship incubation systems and support more intelligent approaches to industry collaboration and policy design (Obschonka & Audretsch, 2020; Roundy & Asllani, 2024). For example, AI can intelligently match entrepreneurial projects with mentors, funding, and resources, optimizing university-led entrepreneurial support services and increasing students' chances of entrepreneurial success (Bell & Bell, 2023; Roundy & Asllani, 2024). In addition, university science parks and incubators are increasingly adopting AI-powered project selection and investment decision-making systems to improve resource allocation efficiency (Jing & Jan, 2022; Thottoli et al., 2024). For instance, AI-driven business plan analysis tools can automatically assess the feasibility of student startup projects, providing data-driven support for entrepreneurship competitions and incubator programs (Chen et al., 2024; Voronov et al., 2023). Regarding government policies, AI is being leveraged to evaluate the impact of EE and optimize policy formulation, ultimately enhancing the effectiveness of entrepreneurship support systems (Valle-Cruz et al., 2020; Weng et al., 2025). These findings suggest that GAI is crucial in enhancing the entrepreneurial ecosystem by improving resource allocation efficiency and guiding EE toward a more intelligent and practice-oriented model.

The findings of this study indicate that the application of GAI in EE spans three levels: micro (learning level), meso (capability level), and macro (ecosystem level). At the micro level, AI is primarily applied in classroom instruction, entrepreneurial simulation, market analysis, and the development of entrepreneurial skills (Chen et al., 2024; Giuggioli & Pellegrini, 2023). At the meso level, AI-powered personalized learning, adaptive feedback, intelligent content generation, and data-driven decision-making are the key mechanisms for enhancing entrepreneurial competencies (Mavlutova et al., 2020; Obschonka & Audretsch, 2020; Xu et al., 2022). At the macro level, prior studies suggest that AI contributes to the optimization of university-based entrepreneurship incubation systems, industry-academia collaboration, and intelligent policy support mechanisms (Kang, 2022; Thottoli et al., 2024). These findings are relevant to Research Questions RQ1 and RQ2. Regarding RQ1, they illustrate that GAI applications extend beyond classroom-level interventions to encompass broader ecosystem-oriented functions, such as institutional innovation and strategic decision-making. In terms of RQ2, the reviewed literature highlights that GAI enables more personalized, adaptive, and data-informed instructional models through mechanisms like generative content, intelligent feedback, and real-time learner support, thereby enhancing the efficiency and practice orientation of EE programs.

Beyond its technical and practical contributions, this study also provides important implications for educational theories and pedagogical practices. Specifically, the integration of GAI into EE aligns with constructivist learning theory by enabling learners to actively construct knowledge through personalized and experiential learning pathways. The findings also align with connectivist theory, which emphasizes the role of networks and technology in facilitating knowledge acquisition and collaboration. Pedagogically, GAI supports adaptive instruction, formative assessment, and student-centered learning, all of which are key principles of modern EE. Educators can leverage these insights to design more effective, engaging, and ethically responsible curricula that foster critical thinking, creativity, and autonomy among students. These pedagogical implications suggest that GAI holds the potential to inform both educational theory and pedagogical practice in entrepreneurship contexts, extending beyond mere technological adoption.

4.2. Critical Review of Research: Theoretical Perspectives, Methodological Approaches, and Unresolved Challenges

In recent years, the application of GAI in EE has become a significant research focus. However, existing studies still face considerable limitations in constructing theoretical frameworks, selecting research methodologies, and the depth of research content. This section systematically analyzes the current research landscape on GAI-enabled EE by examining the applicability of theoretical frameworks, methodological limitations, and research gaps. Additionally, it explores potential directions for future research optimization.

4.2.1. Theoretical Foundations and Integrative Frameworks in GAI-Enabled Entrepreneurship Education

Existing research primarily employs three categories of theoretical frameworks to explain the role of GAI in EE: individual behavior and technology adoption theories, entrepreneurial ecosystem and multi-stakeholder collaboration theories, and learning cognition and technological performance theories. While these theories offer valuable perspectives at different levels, they lack systematic integration and have yet to comprehensively reveal the overall impact of GAI in EE. Individual behavior and technology adoption theories focus on analyzing how learners accept and utilize GAI tools, as well as how GAI influences entrepreneurial intentions. The TPB has been widely applied to study how GAI improves ESE through personalized feedback, thereby increasing entrepreneurial intention (Dabbous & Boustani, 2023; Kang, 2022; T. Nuseir et al., 2020). Additionally, the TAM has been used to examine learners' willingness to adopt GAI-assisted tools, with studies indicating that perceived usefulness and perceived ease of use are key determinants of GAI adoption (Alqahtani, 2023).

However, these studies primarily focus on short-term technology adoption processes, while discussions on how GAI contributes to the development of entrepreneurial competence and long-term entrepreneurial success remain limited (Duong et al., 2024; Pramanik & Jana, 2025; Si et al., 2019; Yuriev et al., 2020). Furthermore, research has yet to explore the dynamic adaptation process of GAI-driven EE, such as its potential to facilitate entrepreneurs' decision-making, team collaboration, and innovation capabilities. Entrepreneurial ecosystem and multi-stakeholder collaboration theories primarily examine the application of GAI within entrepreneurial ecosystems, particularly its role in universities, government policies, and industry collaborations. The EET emphasizes resource integration and collaborative innovation, with studies indicating that GAI, as a component of the ecosystem, optimizes entrepreneurial resource matching and strengthens the connection between education and market needs (Roundy & Asllani, 2024). Additionally, the EEF focuses on how external environments influence entrepreneurial behavior, and some studies have explored how GAI supports entrepreneurs' market awareness and adaptability (Davidsson & Sufyan, 2023). However, few studies have investigated the long-term role of GAI in policy support, industry collaboration, and financial resource allocation (Burström et al., 2021; Roundy & Asllani, 2024). Similarly, there is limited research on how GAI optimizes business incubators, government support systems, and industrial cooperation mechanisms (Jorzik et al., 2024). Learning cognition and technological performance theories focus on how GAI improves EE processes and learning outcomes. The Technology Performance Model (TPC) examines the impact of GAI on learning effectiveness and entrepreneurial performance (Marchena Sekli & Portuguez-Castro, 2025). In contrast, the Connectivist Learning Theory (CLT) emphasizes how GAI supports network-based entrepreneurial learning and knowledge sharing (Liang & Bai, 2024). Although some studies have begun applying TPC and CLT, these frameworks remain exploratory and have not yet matured into comprehensive theoretical models. Additionally, current research primarily focuses on how GAI improves short-term learning outcomes, with limited attention to its long-term effects on the development of entrepreneurial competence.

Overall, research on GAI-enabled EE still faces several challenges. First, individual behavior theories primarily address short-term technology adoption but lack in-depth analysis of GAI's role in long-term entrepreneurial skill development. Second, ecosystem theories emphasize university-industry-government interactions yet fail to explore how GAI optimizes industry collaborations, policy support, and funding allocation. Lastly, while learning cognition theories introduce personalized learning mechanisms, they lack cross-level integration frameworks to systematically uncover GAI's multidimensional impact on EE. Future research should establish a more comprehensive theoretical framework integrating technology adoption, ecosystem collaboration, and learning cognition perspectives, allowing for a deeper understanding of GAI's role in EE.

4.2.2. Methodological Approaches: Strengths, Limitations, and Future Directions

Existing research on GAI-enabled EE employs four primary methodological approaches: quantitative research, qualitative research, mixed-method research, and conceptual research, maintaining a balance between empirical analysis and theoretical exploration. However, from a methodological perspective, several limitations persist, affecting a comprehensive understanding of how GAI functions in EE.

Quantitative research primarily utilizes surveys, experiments, and statistical modeling to quantify the impact of GAI on EE. For instance, SEM has been applied to analyze how GAI influences entrepreneurial intention (Dabbous & Boustani, 2023; T. Nuseir et al., 2020), while machine learning techniques have been used to predict the learning effectiveness of GAI in EE (Chen & Aljawarneh, 2022; Shepherd & Majchrzak, 2022). Despite its rigor in causal inference, quantitative research exhibits certain shortcomings. First, data collection methods are limited, as most studies rely on cross-sectional data, failing to capture the long-term impact of GAI on entrepreneurial capability development (Chen et al., 2024; Giuggioli & Pellegrini, 2023). Second, the variable selection remains constrained, with a limited examination of GAI's indirect effects on teaching optimization, resource matching, and entrepreneurial decision-making. This results in an incomplete understanding of GAI's mechanisms in the EE context. Qualitative research primarily employs interviews, case studies, and textual analysis to explore the practical applications of GAI in EE (Kleine et al., 2020; Liang & Bai, 2024; Marchena Sekli & Portuguez-Castro, 2025). For example, Liang and Bai (2024) revealed through interviews how GAI improves entrepreneurial opportunity recognition. However, qualitative research presents several methodological challenges.

First, small sample sizes are a significant limitation, as most studies rely on in-depth interviews with small participant pools, making large-scale validation difficult and restricting the generalizability of findings. Second, the lack of systematic data analysis frameworks leads to subjective data handling, with inadequate coding and logical validation standardization, thereby affecting research reproducibility (Chen et al., 2024; Giuggioli & Pellegrini, 2023). Additionally, insufficient cross-case comparisons have hindered understanding of how GAI adapts across diverse EE settings, limiting its broader applicability. Mixed-method research combines quantitative and qualitative methodologies to provide a more holistic perspective. For example, some studies first conduct interviews to identify key influencing factors of GAI in EE before employing statistical models to validate variable relationships (Torres Ortega et al., 2025; Vecchiarini & Somià, 2023; Zhou et al., 2024).

However, despite its potential, mixed-method research still faces significant constraints. First, most studies focus on small-scale experiments, which limits the depth of research and systematic development, and thereby affects the generalizability of their conclusions. Second, integrating quantitative and qualitative data remains weak, with many studies failing to fully incorporate qualitative insights into quantitative analysis, restricting the ability to understand GAI's dynamic evolution in EE. Furthermore, sample regional limitations pose another challenge, as most mixed-method studies are confined to specific countries or regions, lacking cross-cultural and cross-market comparative analyses. Conceptual research primarily focuses on theoretical frameworks for GAI in EE, proposing new analytical models to support GAI-driven education (Fox et al., 2024; Nowak, 2020; Shepherd & Majchrzak, 2022). However, several issues persist. First, the lack of empirical validation makes some proposed models challenging to apply. Second, inadequate adaptability to dynamic changes has led to limited research on how the continuous evolution of GAI technologies influences long-term EE models. Additionally, insufficient integration of large-scale data analysis has left gaps in understanding how GAI supports long-term learning effectiveness and entrepreneurial practice.

From a methodological standpoint, research on GAI-enabled EE has achieved a certain balance across quantitative, qualitative, mixed-method, and conceptual approaches, but still suffers from several limitations. First, longitudinal data tracking remains insufficient. Quantitative studies should employ longitudinal research designs instead of solely relying on cross-sectional data to capture the long-term impact of GAI on EE. Second, methodological integration is lacking. Mixed-methods research should strengthen the synergy between quantitative and qualitative data to improve the systematization and explanatory power of the findings. Third, predictive modeling and dynamic analysis are underutilized, and future research should incorporate AI-driven predictive modeling, reinforcement learning, and dynamic system analysis to explore GAI's long-term effects on EE. Lastly, cross-cultural applicability is understudied. Future studies should examine GAI's adaptability across different educational systems and economic environments, investigating how policy and market conditions influence the role of GAI in EE. In summary, research on GAI-enabled EE still faces challenges in data sustainability, methodological integration, and empirical validation. Future studies should adopt longitudinal tracking, optimized mixed-method designs, and dynamic modeling to develop a more systematic empirical framework, ensuring a comprehensive understanding of GAI's long-term impact and maximizing its theoretical and practical contributions.

4.2.3. Unresolved Research Challenges and Future Trajectories in GAI-Enabled Entrepreneurship Education

Despite the growing body of research exploring the role of GAI in EE, several critical research gaps persist, particularly in the integration of theoretical frameworks, methodological limitations, and the assessment of long-term impacts. From a theoretical perspective, existing studies predominantly examine the influence of GAI on learners' entrepreneurial intentions; however, its contribution to the development of long-term entrepreneurial competence remains insufficiently explored. Most research relies on single-theory approaches with limited interdisciplinary integration, such as the incorporation of psychological models (e.g., Social Cognitive Theory, SCT) or quantitative entrepreneurial analysis frameworks (e.g., Dynamic Capability Theory, DCT) to construct a more comprehensive understanding of GAI-enabled EE. While research has acknowledged GAI's role in the entrepreneurial ecosystem, studies rarely examine its long-term impact on policy evaluation, government support systems, and industry collaboration. Additionally, although learning cognition theories introduce GAI-powered personalized learning mechanisms, they lack cross-level integration frameworks to reveal GAI's multidimensional effects in EE systematically.

Advancing research in this field requires integrating micro (individual entrepreneurial learning), meso (entrepreneurial competence development), and macro (entrepreneurial ecosystem) perspectives, developing a holistic analytical framework, and exploring multi-theory integration pathways to capture the role of GAI in EE better. Methodologically, several challenges remain. First, quantitative research predominantly relies on cross-sectional data, which limits its ability to assess the long-term influence of GAI on entrepreneurial competence development. A shift toward longitudinal tracking designs and multi-model analysis, such as combining SCT, TPB, and SEM-based entrepreneurship models, would allow for a more nuanced understanding of GAI's sustained impact. Additionally, existing quantitative studies often employ limited variable settings, with insufficient exploration of GAI's indirect effects on educational optimization, resource allocation, and entrepreneurial decision-making. Expanding variable scopes would provide deeper insights into how GAI-driven knowledge construction shapes entrepreneurial decision-making, team collaboration, and market adaptability. Second, qualitative research is often constrained by small sample sizes and subjective analysis methods, which can affect the generalizability and reproducibility of findings. Most studies rely on interviews, case studies, and text analysis, yet the absence of standardized data coding and analysis frameworks weakens research consistency. Applying thematic analysis, grounded theory, or text mining could strengthen the systematic analysis of qualitative data.

Moreover, existing studies primarily focus on individual EE cases, neglecting comparative analyses across institutions, industries, and national contexts. A broader comparative framework would facilitate assessments of GAI's adaptability across different cultural, policy, and economic environments. Third, mixed-methods research remains underdeveloped, with limited integration of quantitative and qualitative data, which restricts systematic analysis. While some studies identify key factors through qualitative interviews and validate relationships via statistical modeling, the linkage between these approaches is often weak. A more structured combination of quantitative and qualitative insights would provide a clearer understanding of GAI's role in EE. Expanding large-scale mixed-methods studies would help bridge this gap, enabling a more comprehensive exploration of GAI's educational impact. Fourth, conceptual research frequently proposes theoretical frameworks without empirical validation, making it difficult to assess the evolutionary trajectory of GAI-enabled EE. Existing models tend to be static, lacking insights into how GAI adapts to technological iterations and market dynamics. Incorporating long-term data tracking and dynamic modeling would provide a deeper understanding of GAI's role in educational processes, entrepreneurial behavior, and ecosystem optimization over time. Moreover, as GAI technology continues to evolve, research has yet to systematically examine technological adaptability and dynamic evolution.

Continuous progress in GAI-powered learning models, content creation, and entrepreneurial decision-making could transform the EE landscape. However, these potential advancements are still underexplored in current research. Using more dynamic empirical methods, such as longitudinal studies or cross-contextual comparisons, to follow the development of GAI technologies may help ensure that theoretical insights remain relevant to practical innovations. This section addresses RQ3 by highlighting ongoing gaps in theoretical grounding, methodological rigor, and practical relevance. Additionally, it proposes strategic research directions aimed at building a more structured and empirically supported understanding of GAI-enabled EE.

4.3. Optimizing Research Methods, Variables, and Empirical Framework for Future Studies

As the application of GAI in EE continues to evolve, current research methodologies remain constrained by limited empirical grounding and inconsistent operationalization of variables. Future studies may benefit from refining methodological designs, clarifying theoretical constructs, and systematically exploring variable relationships to build a more nuanced understanding of GAI's role in EE contexts. This section contributes to addressing RQ4 by examining the methodological limitations identified in the reviewed literature and proposing optimization strategies such as more explicit construct definitions, more robust empirical frameworks, and the integration of multi-level analytical approaches to inform future empirical studies and theoretical development.

4.3.1. Methodological Advancements

Existing research methods on GAI-enabled EE primarily include quantitative, qualitative, and mixed methods approaches, yet they face limitations in fully capturing GAI's impact. Quantitative research relies on cross-sectional data, including surveys, experiments, and statistical modeling, to quantify the influence of GAI on entrepreneurial education. While SEM has been used to analyze GAI's effect on entrepreneurial intention (Dabbous & Boustani, 2023; T. Nuseir et al., 2020), and machine learning has been applied to predict learning effectiveness (Chen & Aljawarneh, 2022; Shepherd & Majchrzak, 2022), existing studies often lack longitudinal tracking, limiting insights into GAI's long-term impact on entrepreneurial competency (Chen et al., 2024; Giuggioli & Pellegrini, 2023). Expanding longitudinal study designs and integrating broader theoretical models can support explanatory depth. SEM remains underutilized despite its capacity to model complex relationships and support latent variable analysis (Manley et al., 2021). While widely applied in EE (Sakaria et al., 2023; Yi & Duval-Couetil, 2022), the integration of this approach into GAI research remains limited.

A more comprehensive SEM framework, incorporating TPB, SCT, Self-Determination Theory (SDT), and DCT, could provide deeper insights into the role of GAI in entrepreneurial cognition, motivation, and skill development. Qualitative research, often employing interviews, case studies, and text analysis, faces challenges such as small sample sizes, subjective coding, and limited cross-case comparisons (Chen et al., 2024; Liang & Bai, 2024). Integrating computational text analysis (CTA), NLP, and machine learning can improve data objectivity and facilitate comparative analysis across educational settings. Mixed-methods research, which combines qualitative insights with quantitative validation, remains underdeveloped and often lacks systematic integration (Torres Ortega et al., 2025; Vecchiarini & Somià, 2023). Embedding qualitative interviews within experiments, combining longitudinal data analysis, and leveraging SEM alongside qualitative findings would improve the understanding of GAI's educational impact. Refining research methodologies is essential to advancing GAI-enabled EE. Expanding SEM applications, incorporating longitudinal study designs, and improving data integration in mixed-methods research will strengthen empirical rigor. Additionally, CTA and NLP techniques can facilitate objectivity in qualitative research, ensuring a more systematic and multidimensional analysis of GAI's role in EE.

4.3.2. Key Variable Refinement

Existing research primarily examines the direct impact of GAI on EI, while its indirect effects through cognitive, emotional, and behavioral pathways remain insufficiently explored. Future studies should refine variable relationships and develop integrative theoretical models to establish a more comprehensive understanding of GAI-enabled EE mechanisms. First, the mediating role of GAI-enabled EE requires further investigation. ESE may be a crucial link between GAI-driven personalized learning feedback and entrepreneurial intention (Zhu & Zhang, 2022). Employing multiple mediation analyses can help uncover how GAI improves entrepreneurial outcomes through ESE and other cognitive constructs, such as opportunity recognition and innovation capability. Additionally, the potential mediation effects of GAI in market analysis, business model optimization, and resource integration merit further validation to establish a more holistic framework. Second, external environmental factors may shape the efficacy of GAI-enabled EE, yet their influence remains underexamined. Policy incentives, social norms, government regulations, enterprise participation, and economic conditions could either improve or constrain GAI's impact on entrepreneurial competence development (Roundy & Asllani, 2024).

To address this gap, applying HLM and interaction analysis can help determine how institutional policies, industry development stages, and corporate collaboration affect the effectiveness of GAI-driven entrepreneurial learning frameworks. For example, understanding whether enterprise partnerships amplify or suppress the role of GAI in shaping entrepreneurial skills is essential for refining education models. Finally, individual differences in learning adaptability warrant deeper investigation. Factors such as digital literacy, entrepreneurial motivation, and technological adaptability may influence the effectiveness of GAI-driven personalized learning pathways. Learners with high digital literacy are likely to benefit more from GAI-supported EE, whereas those with lower technological proficiency may encounter barriers to adoption (Thanasi-Boçe & Hoxha, 2024). To improve inclusivity, employing group-based experiments and computational text analysis can optimize GAI's adaptability across diverse learner profiles, thereby addressing potential disparities in digital access. SEM, HLM, and interaction analysis should be leveraged to advance this field, refining variable relationships and developing a comprehensive theoretical framework. Further empirical investigations into GAI's long-term impact on the development of entrepreneurial competence and business success rates are also essential. Such inquiries will deepen the theoretical understanding of GAI-enabled EE and provide critical insights for optimizing its practical applications.

4.3.3. Empirical Research Framework

Establishing a more robust empirical research framework may help systematically examine how GAI can support EE and improve research rigor. First, the mixed-methods approach should integrate quantitative experiments, interviews, and case studies to construct a comprehensive causal chain. Experimental studies can control GAI intervention to assess its impact on entrepreneurial skills, innovation, and decision-making. At the same time, interviews can provide valuable insights into learners' perceptions of GAI tools, thereby supporting the explanatory depth. Longitudinal studies should complement cross-sectional data to capture the long-term effects of GAI in EE. Second, data analysis methods require further refinement. SEM remains the dominant approach, yet its application in this domain is still limited. Expanding SEM models by integrating TPB with SCT and SDT can provide a more comprehensive understanding of how GAI influences ESE, opportunity recognition, and entrepreneurial success rates.

Additionally, HLM and interaction analysis may help examine how external factors such as policy incentives, cultural norms, and government regulations moderate the effectiveness of GAI-supported EE. Randomized controlled trials (RCTs) can also be employed to compare the efficacy of GAI-supported pedagogical strategies (e.g., personalized feedback vs. conventional instruction) in improving entrepreneurial competence, thereby strengthening causal inference. To evaluate educational impact, experimental designs with control and treatment groups can be used to compare learning outcomes, such as skill development and business performance. These approaches can provide more substantial evidence regarding the potential value of GAI-supported strategies in EE settings. Cross-cultural and cross-national studies are also crucial for supporting the generalizability of findings. For instance, combining HLM with SEM can enable the examination of how national-level factors such as governmental support, economic structure, or educational policy shape the effects of GAI in EE contexts. Example questions include: Does institutional support the efficacy of GAI-powered EE? Are GAI applications more effective in market-driven versus state-led economies? This section directly addresses RQ4 by outlining methodological pathways for advancing the empirical study of GAI-supported EE. These include multilevel modeling, method integration, causal inference designs, and comparative research across diverse socio-educational systems. By leveraging mixed methods, longitudinal tracking, and cross-contextual analysis, future studies may establish more rigorous empirical foundations to advance both theoretical understanding and practical applications of GAI in EE.

Future research should also empirically test specific hypotheses derived from the reviewed theories, such as how ESE mediates the relationship between GAI-supported personalized feedback and entrepreneurial intention, or how institutional support moderates the effectiveness of GAI in enhancing entrepreneurial skills. Experimental designs comparing GAI-driven and traditional teaching strategies across different cultural and policy contexts would provide more substantial evidence for the generalizability of findings. Longitudinal studies tracking the impact of GAI adoption on entrepreneurial success rates over time could further validate the dynamic role of GAI in EE.

In addition to methodological and theoretical advancements, the findings of this review offer practical guidance for stakeholders in EE. For educators, designing GAI-supported curricula should focus on aligning personalized feedback and adaptive simulations with learning objectives, ensuring that students develop critical thinking and entrepreneurial decision-making skills, rather than relying too heavily on AI outputs. For policymakers, supporting the integration of GAI into EE requires investment in teacher training, clear guidelines for the ethical use of AI, and policies that foster equitable access to AI tools. For researchers, future studies should prioritize cross-institutional and cross-cultural comparisons to identify best practices and contextual adaptations of GAI-supported learning environments. These actionable recommendations aim to translate theoretical insights into concrete strategies for improving practice.

To visually consolidate the major insights of this systematic review and illustrate how GAI is shaping EE, Figure 9 presents an integrated thematic framework titled "Emerging Conceptual Domains in GAI-Enabled Entrepreneurship Education." This framework synthesizes findings from the 50 reviewed studies into four intersecting domains: GAI Applications, Teaching & Learning, Entrepreneurial Competency, and Ecosystem & Institutional Readiness, with the central convergence point highlighting key themes in GAI-related EE research. Each domain captures a distinct yet interrelated aspect of how GAI is embedded in educational contexts, ranging from instructional tools and personalized learning pathways to broader governance mechanisms and behavioral outcomes. The framework also identifies critical research gaps, including limited empirical validation, cross-cultural inconsistencies, and underdeveloped behavioral pathways, thus offering a conceptual roadmap for future empirical inquiry and theory development. As such, this visualization not only reflects current knowledge structures but also provides a foundation for future research and practice in this rapidly evolving field.

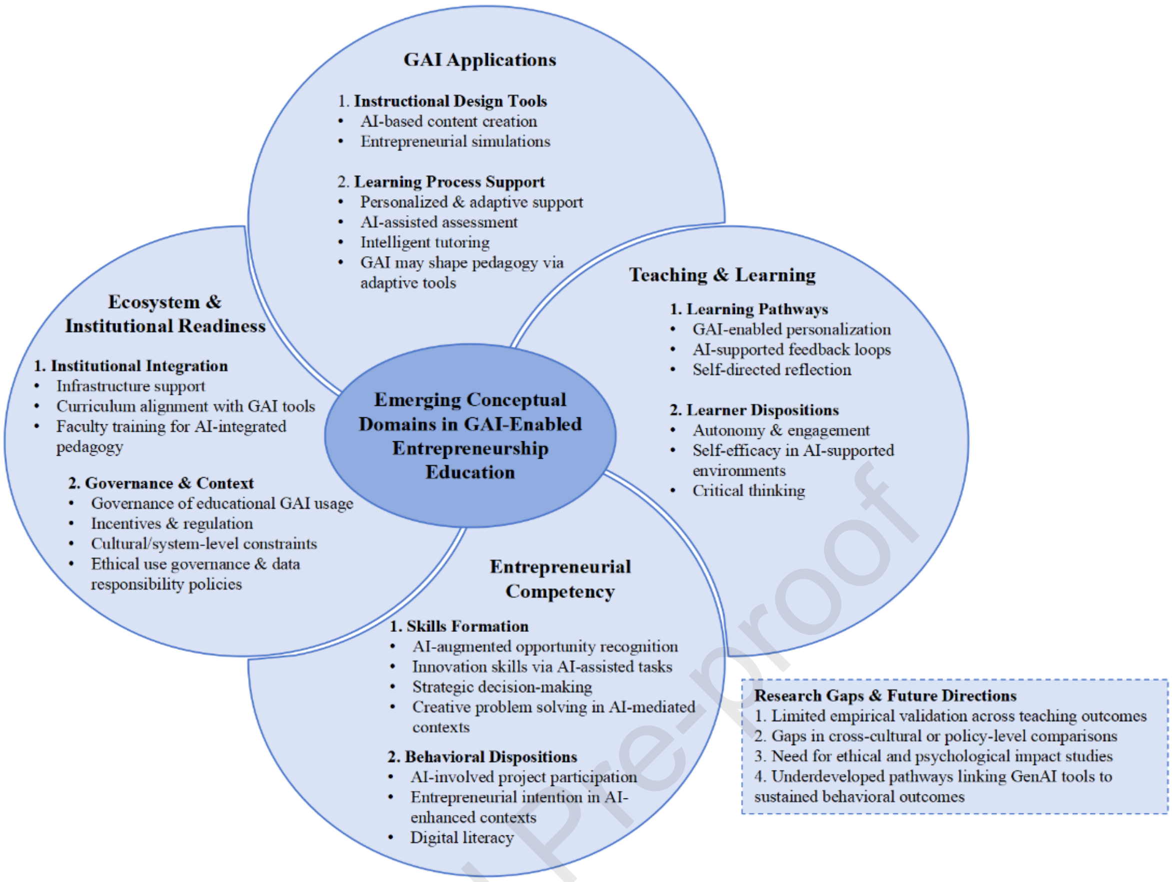

Figure 9. Emerging Conceptual Domains in GAI-Enabled Entrepreneurship Education.

5. Conclusion

This study systematically examined the role of GAI in EE, addressing key questions regarding its application, integration into teaching, research trends, and influencing factors. By synthesizing findings from 50 peer-reviewed publications, this review offers an overview of how GAI may contribute to the evolution of entrepreneurial learning. The findings highlight both the theoretical and practical implications of AI-driven learning environments, while acknowledging existing challenges and limitations. The following sections summarize the key theoretical contributions, practical implications, research gaps, and future research directions identified in this review.

5.1. Theoretical Contributions

This study advances the theoretical understanding of GAI-enabled EE by synthesizing evidence across three distinct levels: the micro level (teaching and learning processes), the meso level (entrepreneurial competency development), and the macro level (support for entrepreneurial ecosystems). At the micro level, GAI improves teaching and learning by enabling personalized, interactive, and intelligent learning environments that foster student engagement and adaptability. At the meso level, GAI facilitates the development of students' entrepreneurial competencies by improving decision-making, opportunity recognition, and innovation capabilities. At the macro level, GAI supports the optimization of the EE ecosystem by improving resource allocation and fostering collaboration among universities, incubators, and industry stakeholders. By systematically reviewing 50 peer-reviewed studies, this review addresses gaps in the literature by exploring the mechanisms through which GAI may support the development of EE, offering a comprehensive, multi-level conceptualization of its impact. These insights enrich existing theories by integrating behavioral, competency-based, and systemic perspectives, laying the groundwork for refining theoretical frameworks and guiding future empirical research on AI-driven entrepreneurial learning.

5.2. Practical and Pedagogical Implications

The findings of this review offer actionable guidance for key stakeholders in EE, while also contributing to pedagogical theory by aligning GAI integration with established educational frameworks. For educators, GAI-enabled curricula should be designed to align personalized feedback and adaptive simulations with learning objectives, fostering students' critical thinking, creativity, ethical awareness, and autonomy. These pedagogical implications resonate with constructivist, experiential, and connectivist learning theories, which emphasize learner-centered, collaborative, and active knowledge construction. Specifically, GAI-supported learning environments support constructivist principles by enabling students to engage with context-relevant, personalized content, promoting experiential learning through immersive simulations and adaptive feedback, and facilitating connectivist learning by helping students build and navigate knowledge networks via collaborative platforms and AI-mediated interactions. For policymakers, supporting GAI-enabled EE requires investment in teacher training, development of ethical guidelines for AI use, and ensuring equitable access to AI technologies to reduce potential disparities among learners. For researchers, cross-institutional and cross-cultural studies are recommended to identify best practices and contextual adaptations of GAI-enabled educational models, as well as to develop evidence-based strategies for scaling their implementation. These practical and pedagogical implications translate theoretical insights into concrete strategies, enabling the design of learner-centered, adaptive, and ethically responsible EE in the digital era.

5.3. Research Gaps and Limitations

Despite providing a systematic literature review and theoretical framework, this study has several limitations. First, the analysis is based on 50 selected peer-reviewed papers, which, while covering key applications of GAI in EE, may not fully capture the latest developments in this rapidly evolving field. Potential publication bias may also lead to an overrepresentation of GAI's positive effects, while underreporting its drawbacks, such as increased student dependence, concerns about academic integrity, and ethical challenges. Future studies should incorporate unpublished datasets, industry reports, and real-world educational experiments to provide a more balanced perspective. Second, the generalizability of the findings is limited by the fact that most reviewed studies focus on higher education, particularly at the university level. The applicability of these approaches to other contexts, such as vocational training, informal learning, or culturally diverse educational environments, remains uncertain. Expanding research to include longitudinal and cross-cultural analyses would provide deeper insights into the sustained impact and adaptability of GAI-enabled EE. Third, methodological limitations should be acknowledged. This study employs thematic analysis to synthesize existing research and identify key trends; however, it does not include a meta-analysis, which could provide a quantitative assessment of GAI's influence. Moreover, reliance on prior research limits the ability to establish causal relationships. Future research should integrate systematic meta-analyses and longitudinal empirical studies to validate the mechanisms through which GAI improves entrepreneurial competencies and outcomes. By addressing these gaps, subsequent research can strengthen the scientific rigor of GAI-enabled EE and improve its practical relevance.

5.4. Future Research Directions

To further advance the field of GAI-enabled EE, future research should focus on empirically testing theoretical mechanisms and validating structural models through longitudinal and cross-cultural designs. We propose the following research propositions to guide subsequent studies. Research Proposition 1: The effect of GAI-enabled personalized feedback on entrepreneurial intention is mediated by entrepreneurial self-efficacy and moderated by institutional support, digital literacy, and prior entrepreneurial experience. Future studies could test this proposition using SEM and randomized controlled trials, comparing GAI-driven and traditional instructional strategies to establish causality and assess long-term outcomes. Research Proposition 2: The effectiveness of GAI-enabled EE varies across cultural and contextual settings, influenced by macro-level factors such as government support, economic conditions, and cultural norms. Future research could apply HLM and Hofstede's Cultural Dimensions Theory to examine how uncertainty avoidance, collectivism, and digital infrastructure moderate learners' trust in GAI and their collaborative behaviors. Research Proposition 3: Individual differences, including digital literacy, entrepreneurial experience, and learning motivation, moderate the impact of GAI-enabled learning on entrepreneurial competencies. Incorporating theoretical frameworks such as SDT, SOR, and SCT can help explain how GAI meets learners' psychological needs, improves intrinsic motivation, and strengthens perceived behavioral control. In summary, advancing empirical validation, longitudinal tracking, cross-cultural comparisons, and theory-driven research will refine conceptual models and optimize the practical applications of GAI in EE. By leveraging advanced quantitative methods, cross-national datasets, and experimental designs, future studies can make significant contributions to both theoretical and practical research.

Appendix. A. Mapping Scheme for Data Extraction.

Category	Description	Example Codes / Variables
1. Publication Details	Metadata and bibliographic information are used to identify the context and scope of the study.	Author(s), Year, Country/Region, Journal Title, Article Type (Empirical/Theoretical), Citation Count
2. Theoretical Frameworks	Theories or models applied or referenced in the study.	TPB, SCT, SDT, Innovation Diffusion Theory, Entrepreneurial Competency Models, Connectivism, etc.

3. Research Methods	Empirical design or methodology used.	Qualitative, Quantitative, Mixed-Methods, Survey, Case Study, SEM, RCT, Thematic Analysis, etc.
4. GAI Application Domains	Contexts and purposes of GAI use in entrepreneurship education.	Personalized Feedback, AI Tutoring, Simulation-based Learning, Assessment Automation, ChatGPT as Co-pilot
5. Educational Integration	How GAI is embedded in instructional strategies.	Curriculum Design, Pedagogical Adaptation, Problem-based Learning, Blended Delivery, Flipped Classroom
6. Learning Outcomes	Reported outcomes or competencies supported by GAI.	Entrepreneurial Self-Efficacy (ESE), Creativity, Critical Thinking, Decision-making, Risk-taking
7. Influencing Factors	Variables moderating or mediating GAI effectiveness.	Institutional Support, Cultural Context, Digital Literacy, Motivation, Ethical Concerns
8. Limitations Noted	Self-reported limitations of each paper.	Small Sample, Short-term Observation, No Control Group, Limited Generalizability
9. Contribution Type	Nature of the contribution made by the paper.	Conceptual Model, Framework Development, Empirical Validation, Pedagogical Implications
10. Relevance to RQs	Linkage to the four research questions in this review.	RQ1: Application, RQ2: Integration, RQ3: Trends, RQ4: Variables/Outcomes

Appendix. B. Score of each paper on quality assessment criteria.

Paper ID	Methodology	Data Collection	Data Analysis	Total	Category
1	1	1	1	3	M
2	1	1	1	3	M
3	1	1	1	3	M
4	1	1	2	4	M
5	1	2	2	5	H
6	1	1	1	3	M
7	2	2	2	6	H
8	1	1	1	3	M
9	1	1	1	3	M
10	2	2	1	5	H
11	1	1	1	3	M
12	1	2	2	5	H
13	1	2	2	5	H
14	2	2	2	6	H
15	1	2	1	4	M
16	1	1	1	3	M
17	1	1	1	3	M
18	1	2	1	4	M
19	2	2	1	5	H
20	1	1	1	3	M
21	1	1	1	3	M
22	1	1	1	3	M
23	2	2	2	6	H
24	1	1	1	4	M
25	2	2	2	6	H
26	1	2	1	4	M
27	2	1	1	4	M
28	1	2	1	4	M
29	1	1	1	3	M
30	2	1	1	4	M
31	1	1	1	3	M
32	1	1	1	3	M
33	2	1	2	5	H
34	2	2	2	6	H
35	2	1	2	5	H
36	2	1	1	4	M
37	2	1	1	4	M

38	1	1	1	3	M
39	1	1	1	3	M
40	1	1	1	3	M
41	1	1	1	3	M
42	2	2	2	6	H
43	1	2	1	4	M
44	1	2	1	4	M
45	3	1	1	3	M
46	1	1	1	3	M
47	1	1	1	3	M
48	2	1	2	5	H
49	1	1	1	3	M
50	1	1	1	3	M

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Declaration of Interest Statement

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.