VOCATECH: Vocational Education and Technology Journal 7, 2 (2025): 49-64
Website: http://ojs.aknacehbarat.ac.id/index.php/vocatech/index
ISSN 2716-5183 (online) ISSN 2686-4770 (print)

THE NEW EDUCATIONAL FRONTIER: AGENTIC AI'S EVOLUTIONARY JOURNEY THROUGH THE LENS OF SPAR-4-SLR

Sugeng Rifqi Mubaroq[1]*
Mokhamad Arfan Wicaksono[2]
Sherly Rahmawati[3]
Iyan Gustiana[4]
Meiry Akmara Dhina[5,6]

[1]Program Studi Bisnis Digital, Akademi Digital Bandung
Jl. Rancamekar Blok Lio, Bandung, 40292, INDONESIA.

[2]Program Studi Teknologi Rekayasa Perangkat Lunak, Akademi Digital Bandung
Jl. Rancamekar Blok Lio, Bandung, 40292, INDONESIA.

[3]Department of Technical and Vocational Education, School of Postgraduate,
Universitas Pendidikan Indonesia
Jl. Dr. Setiabudi No.229, Kota Bandung, Jawa Barat 40154, INDONESIA.

[4]Faculty of Computer Science, University Malaysia Terengganu
Kuala Terengganu, Terengganu, MALAYSIA.

[5]Faculty of Mathematics and Science Education, Universitas Pendidikan Indonesia,
Jl. Dr. Setiabudi No.229, Kota Bandung, Jawa Barat 40154, INDONESIA.

[6]Faculty of Mathematics and Science, Universitas Al-Ghifari
Jl. Cisaranten Kulon No.140, Kota Bandung, Jawa Barat 40293, INDONESIA.

Abstract

The emergence of Agentic Artificial Intelligence (AI) represents a fundamental transformation in educational technology, characterized by systems capable of autonomous, adaptive, and proactive operation. This systematic literature review employs the SPAR-4-SLR methodology to analyze 281 publications from Scopus, with 251 articles retained after temporal filtering (2010-2024), revealing the evolutionary trajectory of Agentic AI in education. The analysis identifies three distinct evolutionary eras: the Early Era (2010-2015) characterized by rule-based intelligent tutoring systems exhibiting proto-agentic behaviors, the Transitional Era (2016-2019) marked by enhanced adaptive systems leveraging learning analytics and machine learning, and the Agentic Era (2020-2024) distinguished by sophisticated autonomous systems powered by Large Language Models. Through integrated bibliometric, co-occurrence network, and thematic analyses, the study establishes a conceptual framework encompassing five defining characteristics of Agentic AI: learning initiative, dynamic adaptability, multi-modal interaction, persistence and memory, and collaboration with human actors. Co-citation network analysis reveals the intellectual structure connecting foundational intelligent tutoring research to contemporary generative AI applications. Despite exponential growth in publications, significant gaps persist in theoretical conceptualization of agency, longitudinal impact evidence, and implementation across diverse educational contexts, particularly at primary education levels. This study provides a comprehensive research agenda addressing theoretical, methodological, and implementation gaps to advance the effective and equitable development of Agentic AI in education.

Keywords:
Agentic AI; education; artificial intelligence; personalized learning; SPAR-4-SLR.

Abstrak

Kemunculan Agen Artificial Intelligence (AI) merepresentasikan transformasi fundamental dalam teknologi pendidikan, yang dicirikan oleh sistem yang mampu beroperasi secara otonom, adaptif, dan proaktif. Tinjauan literatur

Citation in APA Style: Mubaroq, S. I., Wicaksono, M. A., Rahmawati, S., Gustiana, I., Dhina, M. A. (2025). The new educational frontier: Agentic AI's evolutionary journey through the lens of SPAR-4-SLR. *VOCATECH: Vocational Education and Technology Journal, 7*(2), 227-242.

sistematis ini menggunakan metodologi SPAR-4-SLR untuk menganalisis 281 publikasi dari Scopus, dengan 251 artikel dipertahankan setelah penyaringan temporal (2010-2024), mengungkap trajektori evolusi Agen AI dalam pendidikan. Analisis mengidentifikasi tiga era evolusi yang berbeda: Era Awal (2010-2015) yang dicirikan oleh sistem tutoring cerdas berbasis aturan yang menunjukkan perilaku proto-agentik, Era Transisional (2016-2019) yang ditandai oleh sistem adaptif yang memanfaatkan analitik pembelajaran dan pembelajaran mesin, dan Era Agentik (2020-2024) yang dibedakan oleh sistem otonom yang canggih dan didukung oleh Model Bahasa Besar. Melalui analisis bibliometrik, jaringan ko-okurensi, dan tematik yang terintegrasi, studi ini menetapkan kerangka konseptual yang mencakup lima karakteristik pendefinisi Agen AI: inisiatif pembelajaran, adaptabilitas dinamis, interaksi multi-modal, persistensi dan memori, serta kolaborasi dengan aktor manusia. Analisis jaringan ko-sitasi mengungkap struktur intelektual yang menghubungkan penelitian tutoring cerdas fundamental dengan aplikasi AI generatif kontemporer. Meskipun terjadi pertumbuhan eksponensial dalam publikasi, kesenjangan signifikan masih tetap ada dalam konseptualisasi teoretis mengenai agensi, bukti dampak longitudinal, dan implementasi di berbagai konteks pendidikan, khususnya pada tingkat pendidikan dasar. Studi ini menyediakan agenda penelitian komprehensif yang mengatasi kesenjangan teoretis, metodologis, dan implementasi untuk memajukan pengembangan Agen AI yang efektif dan berkeadilan dalam pendidikan.

Kata Kunci:
Agen AI; pendidikan; kecerdasan buatan; pembelajaran personal; SPAR-4-SLR.

DOI: 10.38038/vocatech.v7i2.249
Received: 02 September 2025; Accepted: 18 December 2025; Published: 22 December 2025

***Corresponding author:**
Sugeng Rifqi Mubaroq, Program Studi Bisnis Digital, Akademi Digital Bandung, Jl. Rancamekar Blok Lio, Bandung, 40292, INDONESIA
Email: mubaroq@digitalbdg.ac.id

1. INTRODUCTION

The educational landscape is undergoing a profound transformation with the integration of Artificial Intelligence (AI) technologies. In recent years, significant advancements in Large Language Models (LLMs) such as ChatGPT and other generative AI systems have spurred the development of "Agentic AI" autonomous, goal-driven systems that can operate independently for extended periods with minimal human supervision, moving beyond passive and reactive tools (Holmes et al., 2022; Kasneci et al., 2023).

Agentic AI refers to autonomous systems that understand broad educational objectives, break them down into smaller instructional tasks, and carry out multi-step pedagogical plans while adapting to learner feedback and changing educational environments (Bandi et al., 2025). Unlike traditional educational AI systems that respond only to single prompts, Agentic AI demonstrates the ability to take on instructional responsibilities from educators, act purposefully in learning contexts, and be accountable for educational outcomes produced. These systems combine strategic planning, persistent memory, external tool integration, and multi-agent collaboration to support learning processes autonomously (Acharya et al., 2025; Hosseini & Seilani, 2025).

Contemporary research demonstrates that agentic characteristics have been developing incrementally in educational AI systems over the past decade. Intelligent Tutoring Systems have evolved from simple rule-based programs to sophisticated systems exhibiting autonomous adaptation, proactive intervention, and goal-directed learning support representing proto-agentic behaviors that have evolved into explicit agentic capabilities through LLM integration (Dai et al., 2024). This evolutionary progression reveals five interconnected characteristics defining Agentic AI in education: learning initiative, dynamic adaptability, multi-modal interaction, persistence and memory, and collaboration with human actors.

Despite growing interest, research on Agentic AI in education faces critical gaps including the lack of unified theoretical frameworks, limited longitudinal studies evaluating long-term impact, and scarcity of research across diverse educational contexts (Alvarado et al., 2025; Liang et al., 2025). This Systematic Literature Review employs the SPAR-4-SLR approach to map the research landscape, identifying trends, gaps, and research opportunities through three research questions:

1. How has Agentic AI evolved in education, and what are the key characteristics that define it?
2. How are agentic capabilities implemented across different educational contexts and application domains?
3. What are the primary research gaps and opportunities for advancing Agentic AI in education?

The main contributions of this study include: (1) the first comprehensive synthesis of Agentic AI research in education across disciplines, (2) a conceptual framework integrating the evolutionary trajectory with five defining characteristics of Agentic AI, (3) systematic mapping of implementation patterns across educational levels and application domains, and (4) the identification of priority research pathways to advance theoretical understanding and practical implementation of this transformative technology.

2. LITERATURE REVIEW

4.1. Theoretical Foundations of Agentic AI in Education

Agentic AI in education is defined as autonomous, goal-driven systems that can operate independently for extended periods with minimal human supervision, moving beyond passive and reactive tools (Bandi et al., 2025). In educational contexts, Agentic AI systems are self-contained, goal-based entities designed to operate autonomously with little human intervention and dynamically respond to shifting educational contexts, ranging from intelligent tutoring systems and adaptive test-taking platforms to autonomous learning companions that provide customized guidance and assistance (Acharya et al., 2025). Unlike traditional AI systems that function as passive or responsive tools, Agentic AI demonstrates the capacity to understand broad educational objectives, break them down into smaller instructional tasks, and carry out multi-step pedagogical plans while adapting to learner feedback and changing educational environments.

The concept of “agency” in Agentic AI refers to the ability to: (1) recognize and represent learning goals, (2) plan and initiate actions to achieve those goals, (3) monitor and evaluate progress, (4) adapt based on feedback and changing conditions, and (5) interact and collaborate with human agents. Agentic workflows built based on LLMs can realize complex tasks in the field of education, allowing the emergence of swarm intelligence through multi-agent collaboration (Dai et al., 2024). What makes agentic AI distinctive in educational contexts is its combination of strategic planning, memory that preserves context over time, external tool integration, and collaboration with other agents to support learning processes.

The development of Agentic AI in education draws on three primary theoretical frameworks which includes pedagogical agent theory, AI-Supported self-regulated learning theory, and complex adaptive systems theory. Pedagogical Agent Theory focuses on the design and implementation of virtual agents that can serve as tutors, mentors, or learning companions. Rooted in human-computer interaction and cognitive psychology research, this theory emphasizes the importance of social and relational aspects of learning interactions (Baylor & Kim, 2005; Kim & Baylor, 2016). The social presence, personification, and emotional responsiveness of agents can influence learner engagement and outcomes.

AI-Supported Self-Regulated Learning Theory addresses how AI can enhance students’ abilities to regulate, monitor, and evaluate their learning. Grounded in Zimmerman’s work, this theory highlights how Agentic AI can act as a metacognitive scaffold, assisting students in setting goals, tracking progress, and adjusting learning strategies (Roll I. & Wylie R., 2016). Complex Adaptive Systems Theory in Education views learning environments as dynamic systems where AI and human agents interact, adapt, and evolve over time. Based on complexity theory principles, this approach emphasizes the emergent and non-linear nature of interactions in Agentic AI-supported learning environments (Jacobson et al., 2016).

4.2. Theoretical Gaps in Agentic AI for Education

Despite significant progress in the development and implementation of Agentic AI, literature analysis reveals three main theoretical gaps:

a. Gap in Theorizing Agency

There is insufficient theoretical clarity regarding the nature and boundaries of "agency" in educational AI systems, evidenced by inconsistent terminology usage across literature. Zawacki-Richter et al. (2019) demonstrate that most research focuses on technological aspects while pedagogical theoretical foundations receive less attention. Furthermore, empirical studies reveal that operational definitions of agency vary significantly across implementations, despite established philosophical frameworks associating agency with autonomous action and intentionality (Frankfurt, 1971; Searle, 2004).

Bandura's social cognitive theory identifies four core features of human agency: intentionality, forethought, self-regulation, and self-reflection (Bandura, 2001), yet systematic application to educational AI remains underdeveloped. Actor-network theory offers an alternative framework for distributed agency (Callon, 1984; Latour, 2005), while Biesta and Tedder propose "ecological agency" as context-dependent achievement (Biesta & Tedder, 2007). However, comprehensive taxonomies for AI agency levels in education and frameworks for agency distribution among AI systems, educators, and learners remain needed (Rammert, 2012).

b. Gap in Integrating Learning Theories and AI Paradigms

A significant gap exists between established learning theories and contemporary AI paradigms. Firstly, constructivist theory emphasizes that knowledge is actively constructed by learners; however, most AI implementations still focus on content delivery or corrective feedback, which are not fully aligned with constructivist principles (Paivia, 2014). Furthermore, Vygotsky's social theory from the Zone of Proximal Development is very relevant for Agentic AI that can act as a "more capable other," but there are still gaps in applying these principles to educational AI system design (Luckin et al., 2022; Vygotsky, 1978). Cognitive Theory also has potential for integration with cognitive model-based AI approaches, such as applying cognitive load theory to optimize information presentation (Sweller, 2011). However, computational cognitive models underlying many educational AI systems are often oversimplified and do not fully capture the complexity of human cognitive processes (MacLellan et al., 2022). Integration between situated learning theories (Lave & Wenger, 1991) and embodied cognition approaches (Shapiro, 2019) with AI paradigms is also limited. Integrative models bridging the gap between AI algorithms and pedagogical theories are needed.

c. Gap in Theorizing AI's Social Role

The current theoretical understanding of AI agents' integration within the social fabric of learning environments remains inadequate. Firstly, the long-term effects of sustained interactions with AI agents on learners' social skill development are insufficiently examined. Furthermore, significant gaps persist regarding how AI's social roles are constructed, negotiated, and evolve within educational contexts, particularly as systems transition from rule-based interactions to sophisticated agentic behaviors.

Current literature lacks systematic approaches to understanding how social presence, trust, and collaborative relationships develop in AI-supported educational environments. Additionally, without robust theoretical foundations for AI's social role, implementations risk undermining natural social learning processes or creating artificial interactions that fail to support authentic educational relationships. There is a pressing need for comprehensive theoretical frameworks that elucidate the social dynamics underpinning AI-mediated learning interactions and their implications for designing and deploying Agentic AI systems in education.

3. METHODS

This study employs a Systematic Literature Review (SLR) based on the SPAR-4-SLR protocol (Scientific Procedures and Rationales for Systematic Literature Reviews) developed by Paul et al. (2021). While PRISMA and PRISMA-P provide comprehensive guidelines for systematic reviews, they were developed for systematic reviews in general and provided little rationales that researchers could use to justify their review decisions (Paul et al., 2021). The SPAR-4-SLR protocol addresses these limitations by integrating four key pillars (Scientific Theory, Procedures, Analyses, and Rationales), specifically developed for systematic literature reviews with emphasis on documenting rationales for each methodological decision, which is particularly important for emerging interdisciplinary fields like Agentic AI in education.

3.1. SPAR-4-SLR Protocol

The SPAR-4-SLR protocol consists of three main phases: (1) Assembling, (2) Arranging, and (3) Assessing, each with two specific sub-stages, as illustrated in Figure 1. Table A1 in the Appendix provides a detailed implementation of this protocol, along with comprehensive rationales for each methodological decision.

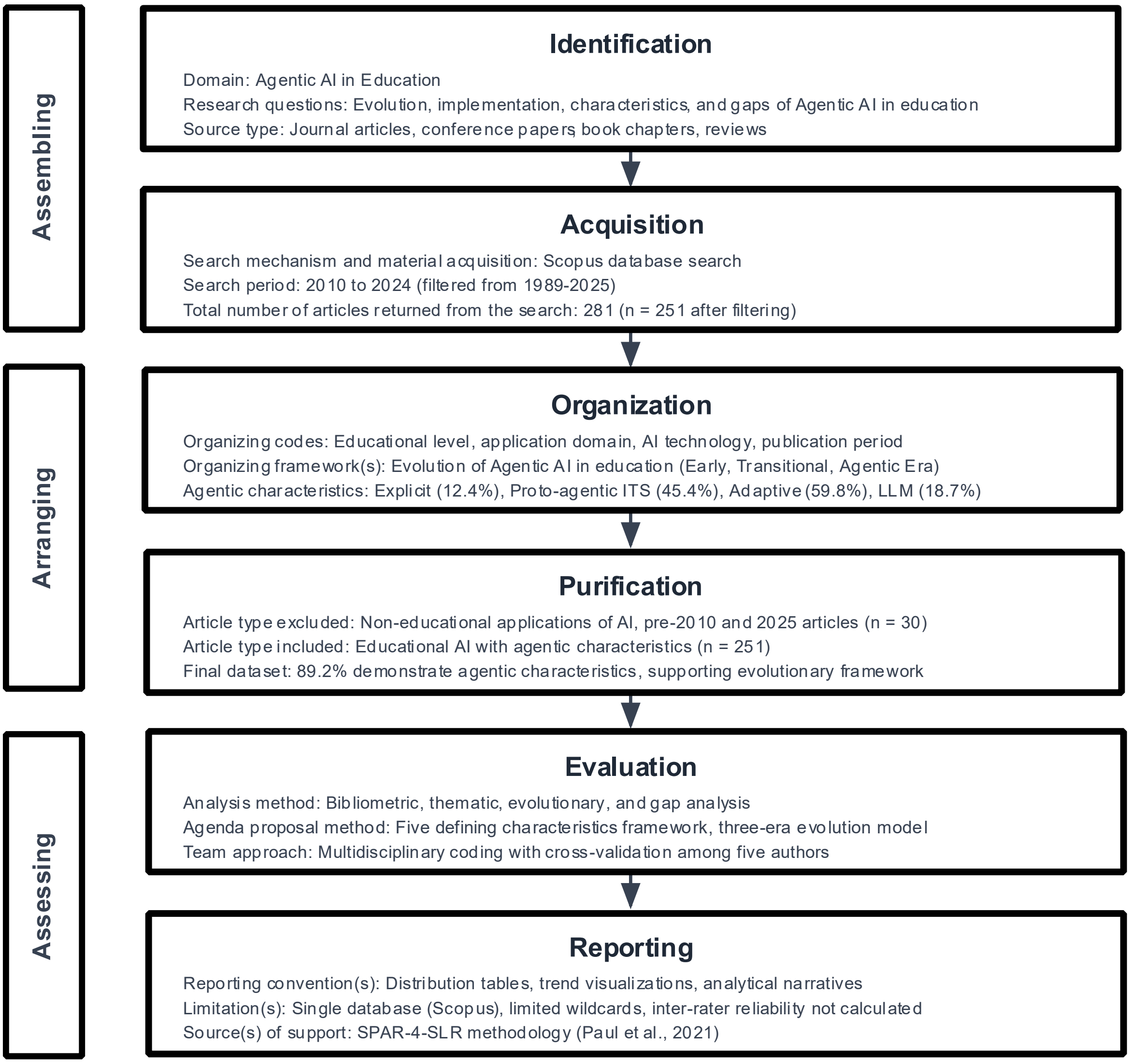

Figure 1. The SPAR-4-SLR Protocol for Agentic AI in Education Research

This section elucidates the comprehensive process of SPAR-4-SLR, encompassing stages from identification to the reporting phase. Furthermore, it provides a detailed account of the analytical tools employed throughout the process. The Assembling phase includes Identification and Acquisition to identify the domain and acquire relevant literature. The Arranging phase encompasses Organization and Purification to organize and refine the literature corpus. The Assessing phase consists of Evaluation and Reporting to analyze and report findings.

3.2. Assembling phase

a. Identification

The research domain is Agentic AI in education, focusing on applications of artificial intelligence exhibiting agentic characteristics (autonomous, proactive, adaptive) in educational contexts. This domain was chosen due to the significant growth in publications, from 20 publications (2010-2015) to 207 publications (2020-2024), indicating rapid development and an urgent need for knowledge synthesis in this field.

Dataset Composition and Evolutionary Approach: The study adopts an evolutionary perspective, examining the development of agentic characteristics in educational AI systems over time. Analysis of the final dataset reveals that while only a small percentage of articles (1.8%) explicitly use "agentic" terminology, the majority of publications (78.6%) focus on Intelligent Tutoring Systems (ITS) and adaptive learning technologies (74.0%) that demonstrate proto-agentic behaviors such as autonomous adaptation, personalized intervention, and goal-directed learning support. Additionally, 18.1% of articles address contemporary LLM-based systems including ChatGPT applications in education, representing the emergence of explicit agentic AI capabilities.

This distribution supports the evolutionary framework, where earlier systems (2010-2019) primarily exhibit foundational agentic characteristics through ITS and adaptive learning, while contemporary systems (2020-2024) demonstrate sophisticated agentic behaviors through LLM integration. The study's scope deliberately includes this evolutionary spectrum to trace how agentic capabilities have developed within educational AI systems, providing comprehensive understanding of the progression from rule-based autonomy to contemporary autonomous agents. The research methodology was designed to systematically address the four research questions outlined in the introduction. Specifically, the chosen approach enables exploration of the temporal dimension (research question 1) through evolutionary and bibliometric analysis, the conceptual dimension (research question 2) through thematic analysis, the interaction dimension (research question 3) through thematic and gap analysis, and the identification of research opportunities (research question 4) through gap analysis. Each research question is linked to specific stages in the SPAR-4-SLR protocol, as shown in Table A1 in the Appendix.

Scopus was selected as the literature source for three primary reasons: (1) it provides access to high-quality peer-reviewed publications across diverse publication types relevant to this interdisciplinary field, (2) its comprehensive metadata supports the bibliometric analysis required to address research questions about the field's evolution, and (3) its broad coverage of leading journals and conferences in AI and education.

b. Acquisition

A systematic search was conducted on the Scopus database using the following search string:

TITLE-ABS-KEY(("Agentic AI" OR "Artificial Intelligence in Education" OR "AI-powered Learning Systems" OR "Adaptive Learning Technologies") AND ("Personalized Learning" OR "Intelligent Tutoring Systems" OR "AI-driven Educational Tools") AND NOT ("Health AI" OR "Medical Applications"))

The TITLE-ABS-KEY field specification ensured that search terms were identified in article titles, abstracts, and author keywords, providing comprehensive coverage of relevant publications. This search string was designed to capture a broad spectrum of publications addressing AI with agentic characteristics in educational contexts while excluding non-educational applications. The selection of keywords was based on a frequency analysis of keywords from related literature, with "artificial intelligence" (62 articles), "personalized learning" (50 articles), and "intelligent tutoring systems" (44 articles) being the most frequently occurring concepts. The use of Boolean operators ("AND", "OR", "AND NOT") aimed to maximize the sensitivity and specificity of the search.

The search was conducted covering the period 1989-2025, yielding 281 documents. To focus on the period when agentic characteristics in educational AI systems began developing, articles were filtered based on temporal relevance. Articles from 1989-2009 (13 articles, 4.6%) were excluded as they preceded the emergence of computational capabilities necessary for sophisticated agentic behaviors in educational systems. Articles from 2025 (16 articles, 5.7%) were excluded due to incomplete publication data and ongoing publication processes at the time of analysis.

The final temporal scope of 2010-2024 was determined based on two considerations: (1) it covers the complete evolution from traditional educational AI systems to contemporary LLM-based applications, and (2) foundational technologies supporting agentic characteristics in educational AI began emerging around 2010. This filtering process resulted in 252 documents (89.7% of total retrieval), ensuring focus on the period when agentic capabilities have developed and matured in educational contexts.

4.3. Arranging Phase

a. Organization

The dataset of 251 articles was organized using a multidimensional coding scheme. The first dimension, educational level, categorized articles based on application context: higher education, secondary school, K-12, primary education, and early childhood education. This categorization was chosen to identify gaps in coverage across educational levels. The second dimension, application domain, classified articles by the primary function of Agentic AI: adaptive virtual tutor, cognitive assistant, metacognitive coach, collaboration facilitator, and evaluator, reflecting the diversity of AI roles in educational contexts. The third dimension, AI technology, identified the technical approaches used: GPT/ChatGPT, machine learning, NLP/LLM, neural networks, and deep learning, to analyze the relationship between technological advancements and agentic capabilities. The fourth dimension, publication period, grouped articles into time intervals: 2010-2015, 2016-2019, 2020-2022, and 2023-2024, to identify temporal trends and address the research question on conceptual evolution.

The coding process involved all five authors with complementary expertise: authors with digital technology backgrounds (Authors 1-2) led AI technology classification, authors with educational backgrounds (Authors 3, 5) focused on educational level and pedagogical categorization, and the computer science expert (Author 4) contributed to application domain analysis. The coding framework employed systematic content analysis based on predefined dimensions derived from the SPAR-4-SLR organizing criteria, ensuring consistency across the multidisciplinary team. Cross-validation was conducted through collaborative discussion sessions among all authors to resolve classification disagreements.

Agentic Characteristics Classification Framework

To systematically analyze the evolutionary development of agentic capabilities, articles were classified based on the presence of agentic characteristics rather than explicit "agentic" terminology. This classification recognizes that agentic behaviors have been developing in educational AI systems before the widespread adoption of "agentic AI" terminology. The framework categorizes systems based on demonstrated capabilities:

1. Explicit Agentic AI (12.4% of dataset): Articles explicitly using "agentic," "agency," "agent," "autonomous," or "proactive" terminology in educational AI contexts
2. Proto-Agentic Systems (45.4% of dataset): Intelligent Tutoring Systems demonstrating autonomous adaptation, personalized intervention, and goal-directed behaviors
3. Adaptive Learning Systems (59.8% of dataset): AI systems exhibiting dynamic adaptability and personalized learning capabilities
4. Contemporary Agentic Systems (18.7% of dataset): LLM-based systems including ChatGPT applications demonstrating sophisticated agentic behaviors.

This classification framework enables analysis of the evolutionary trajectory from basic autonomous behaviors to sophisticated agentic capabilities, providing empirical foundation for understanding how agentic characteristics have emerged and developed in educational AI systems over the study period.

Dataset Analysis and Categorization

Following data collection, comprehensive content analysis was conducted to understand the composition and characteristics of the retrieved literature. Each article was systematically analyzed for:

1. Explicit Agentic Terminology: Presence of terms such as "agentic," "agency," "agent," "autonomous," "proactive" in titles, abstracts, and keywords
2. Agentic Characteristics: Evidence of autonomous behavior, goal-directed action, adaptive responses, and proactive intervention capabilities
3. Technology Classification: Underlying AI technologies including ITS, adaptive learning systems, machine learning, NLP, and LLM applications
4. Temporal Evolution: Changes in agentic capability sophistication across the study period

This analysis revealed that 89.2% of articles demonstrate various degrees of agentic characteristics, supporting the evolutionary framework adopted in this study. The distribution includes explicit agentic terminology in 12.4% of articles, proto-agentic behaviors in Intelligent Tutoring Systems (45.4%), adaptive learning capabilities (59.8%), and contemporary LLM-based implementations (18.7%). The significant overlap among categories reflects the integrated nature of agentic capabilities, while 10.8% of articles address general AI in education without specific agentic characteristics.

The organizing framework developed a temporal evolution model, dividing the literature into three eras based on the dominant characteristics of AI systems, supported by this empirical analysis of content distribution.

b. Purification

Articles were filtered based on inclusion and exclusion criteria (Table 2). Of the 281 documents initially retrieved, 30 articles (10.7%) were excluded based on temporal criteria, resulting in a final dataset of 251 articles from 2010-2024. The distribution of document types in the final dataset included 105 conference papers (42%), 80 articles (32%), 27 book chapters (11%), 18 reviews (7%), and 22 conference reviews (8%).

Table 1. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Publications addressing AI in educational contexts	Publications primarily focused on non-educational contexts
Publications focusing on the "agentic" aspects of AI systems	Publications discussing AI solely as a passive tool without autonomous features
Publications in English	Non-academic publications
Peer-reviewed publications (journals, conferences, books)	Publications focused on health or medical AI applications
Publications from 2010-2024	

3.4. Assessing Phase

a. Evaluation

Four complementary analysis methods were implemented for a comprehensive exploration of the literature. Bibliometric analysis focused on publication trends, geographic distribution, international collaboration patterns, and key publication sources, providing a structural overview of the field's development. Thematic analysis identified and categorized five key features of Agentic AI in education, exploring the conceptual characteristics defining the field. Evolutionary analysis mapped changes in Agentic AI concepts and technologies over time, highlighting the shift from rule-based to autonomous and proactive systems. Gap analysis identified under-researched areas in research focus and methodological approaches, forming the basis for a future research agenda.

This multi-method approach enabled triangulation of findings and a comprehensive exploration of the Agentic AI field from multiple perspectives.

b. Reporting

The analysis results are presented through a combination of three reporting formats. Distribution tables present the classification of articles across various analysis dimensions. Trend visualizations illustrate temporal evolution and patterns in the dataset, clarifying shifts in research focus. Analytical narratives interpret the findings and connect them to the research questions, providing context and meaning to quantitative data.

These reporting formats were chosen to present findings in a comprehensive yet accessible manner. Methodological limitations include reliance on a single database, limited forward citation analysis, and potential bias in thematic categorization. The search strategy did not employ wildcards, which may have limited capture of singular/plural variations of key terms. Additionally, the search focused primarily on publications explicitly using "education" as a keyword, potentially missing relevant studies using alternative educational terminology such as "school," "student," "classroom," or "teaching." Additionally, formal inter-rater and inter-coder reliability statistics were not calculated, though collaborative cross-validation among the multidisciplinary author team was employed to ensure coding consistency.

Dataset Composition Findings: The final dataset demonstrates that 89.2% of articles exhibit at least one agentic characteristic, confirming the evolutionary framework's validity. While this composition supports examining the development of agentic characteristics over time, the significant overlap among categories (45.4% ITS, 59.8% adaptive learning, 18.7% LLM-based, 12.4% explicit agentic terminology) reflects the integrated nature of agentic capabilities rather than discrete system types. The temporal distribution shows significant growth in recent years (82.5% of articles from 2020-2024), which may introduce recency bias in findings. Nevertheless, the applied SPAR-4-SLR methodology ensures the reliability of findings, facilitates reproducibility, and supports research transparency

4. RESULTS AND DISCUSSIONS

4.1. Overview of the Research Landscape

Bibliometric analysis of 281 publications from the Scopus database reveals significant growth in research addressing AI systems with agentic characteristics in educational contexts. Following the temporal filtering described in the Methods section, 251 articles from 2010-2024 form the analytical corpus, excluding 14 articles from 1989-2009 and 16 articles from 2025 due to incomplete publication data.

The growth pattern demonstrates exponential development, with publications increasing from 17 articles (2010-2015) to 27 articles (2016-2019) and dramatically escalating to 207 articles (2020-2024). This growth correlates strongly with the emergence of Large Language Models, particularly evident in the jump from 36 publications in 2023 to 119 publications in 2024—representing a 230% increase that coincides with widespread ChatGPT adoption in educational contexts.

Dataset Composition Analysis: Comprehensive analysis of the 251 filtered articles reveals that 89.2% demonstrate at least one agentic characteristic, validating the evolutionary framework. The distribution includes: 31 articles (12.4%) with explicit agentic terminology (agentic/agency/agent), 114 articles (45.4%) addressing Intelligent Tutoring Systems with proto-agentic behaviors, 150 articles (59.8%) focusing on adaptive and personalized learning systems, and 47 articles (18.7%) examining contemporary LLM-based applications including ChatGPT. This composition supports the evolutionary perspective where agentic characteristics developed incrementally within educational AI systems, with significant overlap among categories reflecting the integrated nature of agentic capabilities.

The research landscape is dominated by a few countries: the United States (52 publications), India (32), China (24), and the United Kingdom (18). Document types reflect a field in active development, with conference papers (42%, 105 publications) and journal articles (32%, 80 publications) comprising the majority. Analysis of AI technologies shows dominance of GPT/ChatGPT (58 articles) and NLP/LLM (56 articles), confirming the shift toward generative language models in recent years.

The intellectual structure of the field, revealed through co-citation network analysis (Figure 2), shows four main clusters representing distinct research traditions: foundational intelligent tutoring systems (purple cluster, centered on (VanLehn, 2011)), paradigmatic transformations (blue cluster, (Roll I. & Wylie R., 2016)), contemporary developments (red cluster, (Chen et al., 2020)), and bridging research (green cluster, 2016-2020). The chronological pattern provides empirical evidence for the evolutionary framework from proto-agentic to explicit agentic systems.

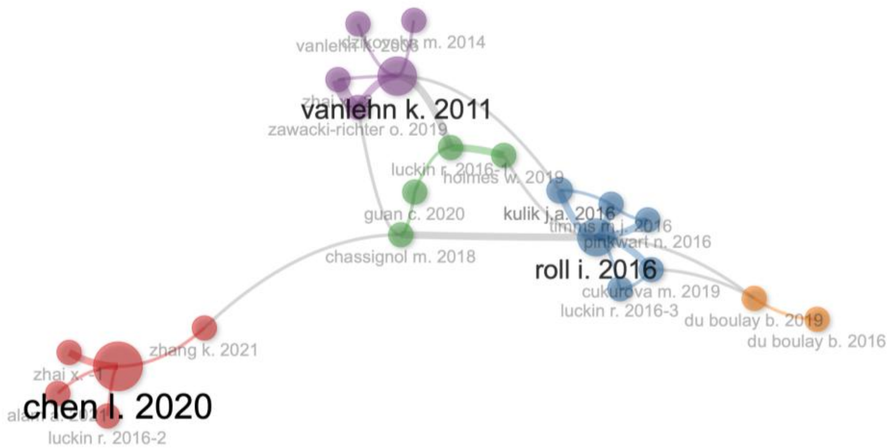

Figure 2. Co-citation network of key literature in the field of Agentic AI for education

4.2. Evolution and Defining Characteristics of Agentic AI

a. Three Eras of Agentic Development

Educational AI systems have evolved through three distinctive eras, each characterized by increasing levels of agency and autonomy. This evolutionary framework addresses the apparent inclusion of "non-Agentic AI" publications by recognizing that agentic characteristics have developed incrementally over time, with early systems exhibiting proto-agentic behaviors that evolved into explicit agentic capabilities.

The Early Era (2010-2015) contained 17 articles representing systems with basic autonomous behaviors including programmed adaptation and rule-based personalization. These foundational systems demonstrated proto-agentic characteristics through automatic progression and basic feedback mechanisms, though lacking sophisticated decision-making capabilities.

The Transitional Era (2016-2019) encompassed 27 articles showing enhanced adaptive systems with data-driven personalization based on learning analytics and machine learning. This period marked the development of more sophisticated autonomous behaviors including real-time adaptation to learner patterns and improved cross-session persistence.

The Agentic Era (2020-2024) comprises 207 articles (82.5% of the filtered dataset) characterized by systems demonstrating explicit agentic capabilities including autonomous initiation, independent decision-making, and sophisticated collaboration. The dramatic growth from 28 publications in 2022 to 119 in 2024 reflects the transformative impact of LLMs and generative AI technologies, particularly ChatGPT, on educational AI development.

b. Conceptual Development and Theoretical Significance

The co-occurrence network analysis (Figure 3) reveals the conceptual progression supporting the five-characteristic framework of Agentic AI. The red cluster (center) demonstrates the evolution of core concepts from "intelligent tutoring system" and "adaptive learning" toward "personalized learning" and "artificial intelligence in education," reflecting the development of learning initiative and dynamic adaptability characteristics. The green cluster (bottom left) highlights natural language processing technologies enabling multi-modal interaction capabilities. The blue cluster (top) features contemporary concepts including "chatgpt," "large language model," and "generative artificial intelligence," representing the emergence of sophisticated persistence, memory, and collaboration capabilities.

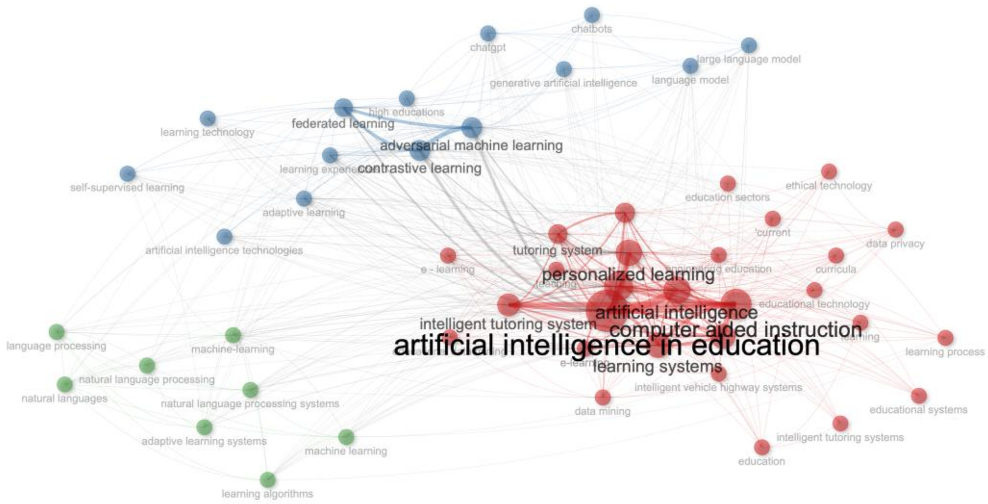

Figure 3. Co-occurrence network of keywords in Agentic AI research for education, showing three main clusters and relationships among key concepts.

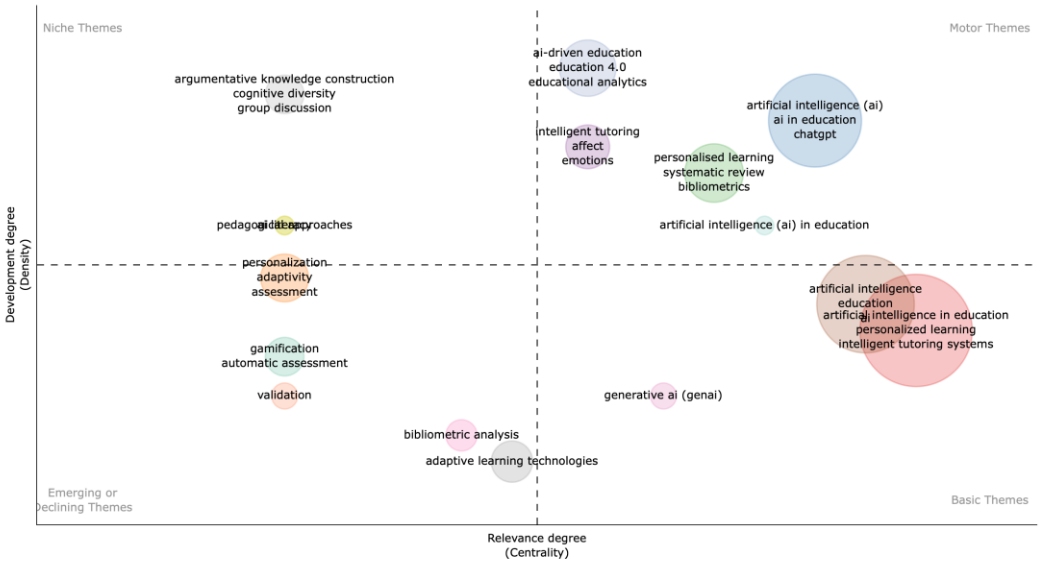

Figure 4. Thematic map showing the positioning of research themes based on centrality (relevance) and density (development level).

This conceptual development is significant for understanding how agentic characteristics have emerged incrementally rather than appearing suddenly. The thematic map (Figure 4) provides strategic positioning showing ChatGPT and AI in education as Motor Themes driving current development, while intelligent tutoring systems and personalized learning represent foundational Basic Themes that enabled agentic evolution. This progression directly supports the research framework by demonstrating how proto-agentic systems provided the foundation for contemporary explicit agentic capabilities.

c. Five Defining Characteristics: Implementation Evidence

Analysis reveals how the five agentic characteristics are implemented across educational systems, addressing the research question regarding implementation across different contexts and domains:

Learning Initiative is implemented through systems that independently identify knowledge gaps and learning needs. Recent implementations include predictive algorithms in systems like PitchQuest that evaluate student performance and provide adaptive feedback without human intervention (Mollick et al., 2024). Implementation occurs across educational contexts through adaptive virtual tutors that proactively suggest learning materials and initiate interventions based on performance analysis.

Dynamic Adaptability implementation involves real-time adjustment to changing learner needs through continuous optimization of learning pathways. Systems achieve this through multi-dimensional personalization encompassing content, pedagogy, and assessment, with adaptive educational simulation environments demonstrating sophisticated real-time adaptation (Mollick et al., 2024). Implementation spans multiple application domains focusing on adaptive virtual tutors and evaluators providing personalized feedback.

Multi-Modal Interaction implementation leverages various communication modalities including text, voice, and visuals to enhance learning engagement. Research demonstrates implementation through AI-generated pedagogical agents in instructional videos affecting learner retention and cognitive load (Lim, 2024), and integration of biometrics and facial emotion recognition in teacher education contexts (Dieker et al., 2024). Implementation requires sophisticated technical integration spanning NLP/LLM technologies and neural networks.

Persistence and Memory implementation maintains evolving learner models across sessions and contexts, building holistic understanding through historical data integration. The von Neumann multi-agent framework demonstrates implementation through memory and processing components facilitating collaborative learning (R. Jiang et al., 2024). Implementation requires robust data management systems enabling cross-session continuity and long-term learner modeling.

Collaboration with Human Actors implementation involves working alongside educators and students within learning ecosystems through different contextual roles. Implementation includes providing insights and feedback to educators on student progress, supporting collaborative activities, and simulating social interactions to enhance motivation (Lane & Schroeder, 2022). Evidence shows implementation across collaboration facilitators and cognitive assistants supporting educational processes.

4.3. Implementation Across Educational Contexts

a. Distribution and Implementation Patterns by Educational Level

Analysis of the 251 articles reveals implementation patterns across educational contexts, though the majority of articles address general educational applications without specifying particular educational levels. The dataset composition shows that educational AI research demonstrating agentic characteristics has primarily focused on broader applications rather than context-specific implementations.

The evolutionary progression from 17 articles (2010-2015) to 207 articles (2020-2024) indicates that implementation research has concentrated on developing core agentic capabilities before specializing in specific educational contexts. Contemporary implementations, particularly the 119 articles published in 2024, reflect the rapid adoption of LLM-based systems across various educational settings.

Implementation challenges vary across educational levels due to differences in technological infrastructure, regulatory considerations, and learner developmental needs. Early childhood and primary education contexts require simplified interfaces and ethical safeguards, while higher education environments can support more sophisticated agentic capabilities due to advanced technological infrastructure and adult learners' capacity for complex AI interaction.

b. Implementation Across Application Domains

The 251 articles demonstrate agentic implementations across five main application domains, each showing distinct approaches for implementing agentic capabilities:

Adaptive Virtual Tutors represent the most prevalent implementation approach, focusing on comprehensive agentic characteristics through personalized instruction and adaptive feedback systems. Implementation involves sophisticated learning initiative through predictive analytics, dynamic adaptability through real-time pathway optimization, and persistence through comprehensive learner modeling. The growth trajectory from the Early Era (2010-2015) to the Agentic Era (2020-2024) reflects successful implementation scaling across educational contexts.

Cognitive Assistants implement focused agentic capabilities emphasizing learning initiative and collaboration with human actors. Implementation supports cognitive capacity expansion through information retrieval, synthesis, and problem-solving assistance, demonstrating how agentic characteristics enhance rather than replace human cognitive processes.

Metacognitive Coaches implement specialized agentic characteristics supporting self-regulation and reflection. Implementation focuses on persistence and memory capabilities to track learning progress over time and provide metacognitive scaffolding, representing emerging applications with significant growth potential.

Collaboration Facilitators implement social agentic characteristics supporting team-based learning through multi-agent collaboration and human-AI interaction. Implementation demonstrates how agentic AI can enhance social learning processes while maintaining authentic human relationships.

Evaluators and Feedback Providers implement assessment-focused agentic capabilities through automated evaluation and personalized feedback systems. Implementation emphasizes learning initiative through proactive assessment and dynamic adaptability through responsive feedback mechanisms.

4.4. Research Gaps and Future Directions

a. Addressing Implementation Challenges

The analysis reveals critical implementation gaps requiring urgent attention. Theoretical Implementation Gaps include insufficient frameworks for implementing distributed agency among AI systems, educators, and learners. Current implementations often struggle with agency distribution, lacking systematic approaches for maintaining appropriate human oversight while enabling meaningful AI autonomy.

Methodological Implementation Gaps are evident in the predominance of short-term implementation studies, limiting understanding of long-term implementation effects. Longitudinal implementation research is crucial for understanding how sustained interaction with agentic systems affects learner development, motivation, and educational outcomes.

Technical Implementation Gaps persist in developing systems that successfully integrate multiple agentic characteristics in coherent, functional implementations. Evidence shows gaps between theoretical agentic potential and real-world implementation capabilities, particularly regarding seamless integration of learning initiative, dynamic adaptability, multi-modal interaction, persistence, and collaboration features.

Contextual Implementation Gaps are highlighted by significant educational level imbalances, indicating successful implementation approaches have not been adapted across diverse educational contexts. Implementation research must prioritize underrepresented levels, developing age-appropriate interaction modalities and context-sensitive agentic features.

b. Comprehensive Research and Implementation Agenda

Future research should address implementation challenges through four strategic directions:

Longitudinal Implementation Studies should track agentic AI implementation impact over extended periods to understand effects on learner motivation, self-regulation, and achievement. Comparative implementation studies could explore different agentic configurations to determine optimal implementation designs for specific educational contexts, examining how varying levels of autonomy and interaction modalities affect implementation success.

Theoretical Implementation Frameworks should develop integrative models bridging implementation gaps between AI algorithms and pedagogical theories. Research should conceptualize optimal agency distribution in implementation contexts, addressing how agentic systems can effectively collaborate with human actors while maintaining educational effectiveness.

Context-Sensitive Implementation Research should prioritize underrepresented educational levels, developing age-appropriate implementation approaches and exploring cultural adaptations for diverse global contexts. Implementation research should investigate informal learning environments and vocational contexts, expanding agentic AI applications beyond formal educational settings.

Evaluation and Standards Development should establish comprehensive implementation assessment frameworks including metrics for evaluating agentic feature effectiveness, implementation success indicators, and standardized benchmarks enabling comparison across systems and contexts.

4.5. Theoretical and Practical Implementation Implications

The evolution from passive educational tools to active agentic partners necessitates reconceptualizing implementation approaches in educational contexts. Findings reveal transformation requirements in learning interactions demanding new implementation models explaining student-educator-AI relationships and role distribution. Successful implementation depends on alignment with institutional structures, cultures, and capacities, requiring phased and contextual implementation strategies.

Implementation considerations include ensuring algorithmic transparency, balancing AI proactivity with user control, and integrating cognitive-metacognitive-affective support through carefully designed agentic features. The significant educational level implementation imbalances underscore needs for differentiated implementation strategies based on context, with particular attention to ethical considerations in applications involving younger learners.

The proposed research agenda provides implementation roadmap for advancing both theoretical understanding and practical deployment of Agentic AI in education. By addressing identified implementation gaps through longitudinal studies, theoretical framework development, contextual implementation research, and comprehensive evaluation methods, the field can progress toward realizing agentic AI's transformative potential while ensuring ethical, equitable, and effective implementation across diverse educational contexts.

5. CONCLUSION

This systematic literature review provides a comprehensive synthesis of Agentic AI's evolutionary journey in education, revealing a paradigm shift from passive educational tools to autonomous learning partners. The SPAR-4-SLR analysis delineates three distinct evolutionary eras that trace the field's transformation: the Early Era (2010-2015) established foundational proto-agentic behaviors through rule-based intelligent tutoring systems, the Transitional Era (2016-2019) advanced adaptive personalization through learning analytics and machine learning, and the Agentic Era (2020-2024) witnessed the emergence of sophisticated autonomous systems powered by Large Language Models. This evolutionary progression, marked by exponential publication growth and the widespread adoption of generative AI technologies, demonstrates how agentic characteristics have developed incrementally within educational AI systems before crystallizing into explicit agentic capabilities. The co-occurrence and co-citation network analyses provide empirical evidence of this conceptual evolution, showing the field's trajectory from intelligent tutoring systems toward personalized learning frameworks and contemporary LLM-based applications.

The study establishes a conceptual framework identifying five interconnected characteristics that define Agentic AI in education: learning initiative, dynamic adaptability, multi-modal interaction, persistence and memory, and collaboration with human actors. This framework emerges from the evolutionary analysis, demonstrating how these characteristics have progressively manifested across different eras and implementation contexts. The systematic mapping of implementation patterns reveals how agentic capabilities are deployed across educational levels and application domains, from adaptive virtual tutors to metacognitive coaches, though with notable imbalances in coverage and contextual adaptation.

Critical gaps remain across theoretical, methodological, and implementation dimensions. Theoretically, ambiguities persist in conceptualizing AI agency in educational contexts, integrating established learning theories with contemporary AI paradigms, and understanding AI's evolving social role within learning environments. Methodologically, the predominance of short-term studies limits understanding of long-term impacts on learner development and educational outcomes. Implementation gaps are evidenced by significant educational level imbalances, with higher education dominating research attention while primary and early childhood education remain severely underrepresented. Geographic disparities further constrain the field's global applicability and equitable access to Agentic AI innovations.

Addressing these gaps requires a concerted research agenda prioritizing four strategic directions: longitudinal studies examining sustained impacts across diverse learner populations, theoretical frameworks integrating AI capabilities with pedagogical principles, context-sensitive implementation research spanning underrepresented educational levels and cultural contexts, and comprehensive evaluation methodologies establishing standards for assessing agentic system effectiveness. This study's contribution extends beyond synthesis to providing a methodological foundation through SPAR-4-SLR and a roadmap for advancing both theoretical understanding and practical implementation. As the field continues its evolutionary trajectory, future research must remain committed to human-centered design principles, ensuring that Agentic AI integration in education is ethical, equitable, and aligned with diverse learner needs across all educational contexts. The transformative potential of Agentic AI can only be realized through systematic efforts addressing identified gaps while fostering inclusive innovation that serves learners globally.

UCAPAN TERIMA KASIH

The author expresses gratitude to the Ministry of Research, Technology, and Higher Education (Kemenristekdikti) for their support through a PDP Research Grant under contract numbers 125/C3/DT.05.00/PL/2025, 8092/LL4/PG/2025, and 192/ADB.WD2/SU/KU/2025.

DAFTAR PUSTAKA

Acharya, D. B., Kuppan, K., & Divya, B. (2025). Agentic AI: Autonomous intelligence for complex goals—a comprehensive survey. *IEEE Access*, *13*, 18912–18936. https://doi.org/10.1109/ACCESS.2025.3532853

Alvarado, A., Aguilar, R., Domínguez-Andrés, J., Angeles, J., Anicas, M., Apacible, K., Arcilla, G., Arcilla, R., & Calacday, C. (2025). Evaluating the effectiveness of AI-generated health educational videos on nursing students' knowledge acquisition of the international patient safety goals (IPSG). *Journal of Interdisciplinary Perspectives*, *3*(10), 222–229. https://doi.org/10.69569/jip.2025.622

Bandi, A., Kongari, B., Naguru, R., Pasnoor, S., & Vilipala, S. V. (2025). The Rise of Agentic AI: A review of definitions, frameworks, architectures, applications, evaluation metrics, and challenges. *Future Internet*, *17*(9), 404. https://doi.org/10.3390/fi17090404

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*(1), 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Baylor, A. L., & Kim, Y. (2005). Simulating instructional roles through pedagogical agents. *International Journal of Artificial Intelligence in Education*, *15*(2), 95–115.

Biesta, G., & Tedder, M. (2007). Agency and learning in the lifecourse: Towards an ecological perspective. *Studies in the Education of Adults*, *39*(2), 132–149. https://doi.org/10.1080/02660830.2007.11661545

Callon, M. (1984). Some elements of a sociology of translation: Domestication of the scallops and the fishermen of St Brieuc Bay. *The Sociological Review*, *32*(1), 196–233. https://doi.org/10.1111/j.1467-954X.1984.tb00113.x

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Dai, L., Jiang, Y.-H., Chen, Y., Guo, Z., Liu, T.-Y., & Shao, X. (2024). Agent4EDU: Advancing AI for education with agentic workflows. *Proceedings of the 2024 3rd International Conference on Artificial Intelligence and Education*, 180–185. https://doi.org/10.1145/3722237.3722268

Dieker, L., Hines, R., Wilkins, I., Hughes, C. E., Scott, K. H., Smith, S., Ingraham, K., Ali, K., Zaugg, T., & Shah, S. (2024). Using an artificial intelligence (AI) agent to support teacher instruction and student learning. *Journal of Special Education Preparation*. https://doi.org/10.33043/d8xb94q7

Frankfurt, H. G. (1971). Freedom of the will and the concept of a person. *The Journal of Philosophy*, *68*(1), 5–20. https://doi.org/10.2307/2024717

Holmes, W., Iniesto, F., Anastopoulou, S., & Boticario, J. G. (2023). Stakeholder perspectives on the ethics of AI in distance-based higher education. *International Review of Research in Open and Distributed Learning*, *24*(2), 96–117. Scopus. https://doi.org/10.19173/irrodl.v24i2.6089

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of ai in education: towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, *32*(3), 504–548. https://doi.org/10.1007/s40593-021-00239-1

Hosseini, S., & Seilani, H. (2025). The role of agentic AI in shaping a smart future: A systematic review. *Array*, *26*, 100399. https://doi.org/10.1016/j.array.2025.100399

Jacobson, M. J., Kapur, M., & Reimann, P. (2016). Conceptualizing debates in learning and educational research: Toward a complex systems conceptual framework of learning. *Educational Psychologist*, *51*(2), 210–218. https://doi.org/10.1080/00461520.2016.1166963

Jiang, R., Chen, Y., Yi, P., Xie, S., & Qu, D. (2024). Opportunities and challenges of AI in vocational education. *International Journal of Learning and Teaching*, *10*(5), 590–596. https://doi.org/10.18178/ijlt.10.5.590-596

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*. https://doi.org/10.1016/j.lindif.2023.102274

Kim, Y., & Baylor, A. L. (2016). Based design of pedagogical agent roles: A review, progress, and recommendations. *International Journal of Artificial Intelligence in Education*, *26*(1), 160–169.

Lane, H. C., & Schroeder, N. L. (2022). Pedagogical agents. *Conference Proceedings*. https://doi.org/10.1145/3563659.3563669

Latour, B. (2005). *Reassembling the social: An introduction to actor-network-theory*. Oxford University Press.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.

Liang, J., Stephens, J. M., & Brown, G. T. L. (2025). A systematic review of the early impact of artificial intelligence on higher education curriculum, instruction, and assessment. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1522841

Lim, J. (2024). The potential of learning with AI-generated pedagogical agents in instructional videos. *Conference Proceedings*. https://doi.org/10.1145/3613905.3647966

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2022). *Intelligence unleashed: An argument for AI in education* (2, Ed.). Pearson.

MacLellan, C. J., Harpstead, E., Patel, R., & Koedinger, K. R. (2022). Discovering how students learn in an intelligent tutoring system: Visualizing model-based learner estimates versus interaction-based algorithms. *Journal of Educational Data Mining*, *14*(1), 1–30. https://doi.org/10.5281/zenodo.6520326

Mollick, E. R., Mollick, L., Bach, N., Ciccarelli, L., Przystanski, B., & Ravipinto, D. (2024). AI agents and education: Simulated practice at scale. *Computers and Society*. https://doi.org/10.48550/arxiv.2407.12796

Paivia, S. (2014). The role of constructivism in a cognitive load theory framework. *Educational Psychology Review*, *26*(2), 225–238. https://doi.org/10.1007/s10648-013-9254-y

Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, *45*(4), O1-O16.

Rammert, W. (2012). Distributed agency and advanced technology. Or: How to analyse constellations of collective inter-agency. In J. H. Passoth, B. Peuker, & M. Schillmeier (Eds.), *Agency without actors? New approaches to collective action* (pp. 89–112). Routledge. https://doi.org/10.4324/9780203834695-8

Roll I. & Wylie R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

Searle, J. R. (2004). *Mind: A brief introduction*. Oxford University Press.

Shapiro, L. (2019). *Embodied cognition*. Routledge.

Sweller, J. (2011). Cognitive load theory. In *Psychology of learning and motivation* (Vol. 55, pp. 37–76). Elsevier.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, *46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Zawacki-Richter O., Marín V.I., Bond M., & Gouverneur F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0