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Research Hotspots and Emerging Trends in AI-Powered Personalized Learning and Academic Performance in Higher Education Using CiteSpace (2015–2025)

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ABSTRACT

Artificial intelligence (AI) is increasingly used to personalize learning and support academic performance in higher education, yet the field's intellectual structure and emerging directions remain fragmented. This study maps the evolution of research hotspots and trends through a scientometric analysis of 193 Web of Science records published between 2015 and 2025. CiteSpace 7.0.1 was used to examine publication growth, country and institutional collaboration, keyword co-occurrence and clustering, timeline patterns, citation bursts, and reference co-citation networks. The findings show rapid expansion after 2023, with China contributing the largest number of publications. Major research themes include intelligent tutoring systems, learning analytics, adaptive learning interventions, deep learning, university transformation, and positive student outcomes. Keyword bursts indicate a shift from rule-based and fuzzy-logic approaches toward adaptive learning, performance evaluation, and generative-AI-supported personalization. Overall, the field is moving toward data-intensive, learner-centred, and outcome-oriented research, while causal evidence, equity, privacy, theoretical integration, and cross-institutional validation remain important priorities.

Keywords: academic performance, artificial intelligence, CiteSpace, higher education, personalized learning

1. INTRODUCTION

1.1 Research Background

Artificial intelligence (AI) has become increasingly embedded in higher education through intelligent tutoring systems, learning analytics, adaptive assessment, automated feedback, educational recommendation, and generative support. These technologies enable institutions to respond more flexibly to differences in students' prior knowledge, learning pace, engagement, and academic needs. Within this context, personalized learning has developed from a supplementary instructional approach into an important application of AI in education. It aims to adjust learning content, pathways, feedback, assessment, and support according to learner characteristics and performance, while academic performance remains one of the principal outcomes used to evaluate its educational value.
The technological foundations of AI-powered personalized learning have evolved considerably. Earlier studies emphasized expert rules, fuzzy reasoning, semantic frameworks, and adaptive educational systems. For example, fuzzy-semantic models combined domain knowledge with learner performance and behavioural information to generate individualized recommendations, while adaptive e-learning systems selected learning materials according to students' learning profiles and individual differences (Nguyen Dinh Hoa Cuong et al., 2018; Alsobhi & Alyoubi, 2019). With the expansion of educational data, research increasingly shifted toward learning analytics, statistical learning, deep learning, and precision education, particularly for predicting

achievement, dropout risk, engagement, and other student outcomes (Tsai et al., 2020; Luan & Tsai, 2021). More recently, generative AI and large language models have expanded personalization through dynamically generated explanations, summaries, exercises, feedback, and conversational assistance (Pesovski et al., 2024; Sajja et al., 2024; Santhosh et al., 2024).
Despite this rapid technological development, the educational effects of AI-powered personalized learning remain uneven and context dependent. Some studies have reported improvements in academic achievement, knowledge retention, motivation, engagement, and self-regulated learning (Eltahir & Babiker, 2024; Wei, 2023). However, other research has found that observed differences in course performance were not always statistically significant, suggesting that technological personalization does not automatically produce measurable academic gains (Lim et al., 2023). A recent scoping review similarly found generally positive evidence while emphasizing variation in intervention design, assessment methods, implementation conditions, and the outcomes examined (du Plooy et al., 2024). These differences indicate that the field should be examined not only in terms of individual system effectiveness, but also through its broader intellectual structure and changing research priorities.
Existing reviews have synthesized specific technologies, applications, and emerging developments in AI-supported learning. Recent studies have examined the design and assessment of AI-based learning tools, the integration of machine learning and generative AI into learning analytics, and the development of personalized learning in higher education (Luo et al., 2025; Rodriguez-Ortiz et al., 2025; Peng & Li, 2025). Nevertheless, conventional reviews may provide limited insight into how research themes are connected, how scholarly attention has shifted over time, and which topics constitute sustained or emerging research fronts. A scientometric approach addresses this limitation by quantitatively mapping publication patterns, collaboration structures, keyword relationships, citation bursts, and reference co-citation networks. Accordingly, the present study applies CiteSpace to examine the evolution of research hotspots and emerging trends in AI-powered personalized learning and academic performance in higher education between 2015 and 2025.

1.2 Research Objectives and Questions

This study aims to examine the development, knowledge structure, research hotspots, and emerging trends of AI-powered personalized learning and academic performance in higher education from 2015 to 2025. Rather than evaluating the effectiveness of a single technology or intervention, the study provides a systematic overview of how this research field has evolved, which countries and institutions have contributed to its development, and how major themes have changed over time. Through publication trend analysis, collaboration analysis, keyword clustering, timeline visualization, citation burst detection, and reference co-citation analysis, the study seeks to identify both established research themes and emerging areas that may shape future investigations.
Accordingly, the following research questions are addressed:
RQ1: What are the publication trends and major geographical and institutional contributors in this field from 2015 to 2025?
RQ2: What major research hotspots and thematic clusters characterize studies on AI-powered personalized learning and academic performance in higher education?
RQ3: How have these research themes evolved over time, and what emerging trends and research directions can be identified?

2. LITERATURE REVIEW

2.1 Development of AI-Powered Personalized Learning

AI-powered personalized learning refers to the use of intelligent technologies to adjust learning content, pathways, assessment, feedback, and support according to students' characteristics, behaviours, and academic progress. Its early development was closely associated with intelligent tutoring systems, adaptive educational environments, semantic technologies, and fuzzy reasoning. These systems generally relied on predefined learner models and instructional rules to recommend suitable materials or activities. For example, fuzzy-semantic frameworks integrated domain knowledge, learner behaviour, and performance information to generate personalized recommendations, while adaptive e-learning systems matched instructional content with learning styles and individual needs (Nguyen Dinh Hoa Cuong et al., 2018; Alsobhi & Alyoubi, 2019).

The growing availability of institutional and behavioural data subsequently shifted the field toward learning analytics, machine learning, and precision education. Rather than adapting content solely through predefined rules, newer systems use historical and real-time data to predict academic achievement, dropout risk, engagement, and learning difficulties. Statistical learning and deep-learning models have therefore become important tools for identifying students who may require additional support and for informing timely instructional interventions (Tsai et al., 2020; Luan & Tsai, 2021).

More recently, generative AI has expanded the scope of personalization. Large language models and intelligent assistants can produce explanations, summaries, exercises, quizzes, feedback, and conversational support in response to individual learner needs. Emerging systems combine learning analytics with generative functions to provide dynamically created materials and personalized learning pathways (Pesovski et al., 2024; Sajja et al., 2024; Santhosh et al., 2024). This development reflects a transition from selecting predetermined resources to generating adaptive learning support in real time.

2.2 Academic Performance and Emerging Research Concerns

Academic performance is one of the most frequently examined outcomes of AI-powered personalized learning. Existing studies have associated AI-supported learning environments with improvements in achievement, motivation, engagement, knowledge retention, and self-regulated learning (Eltahir & Babiker, 2024; Wei, 2023). A scoping review of personalized adaptive learning in higher education also reported generally positive effects on academic performance and engagement, although the findings varied across technologies, disciplines, research designs, and outcome measures (du Plooy et al., 2024).

Nevertheless, positive effects are not consistent across all settings. Some evaluations have found that differences in course scores between adaptive and conventional learning conditions were not statistically significant (Lim et al., 2023). Such mixed evidence suggests that educational outcomes depend not only on the technical sophistication of an AI system but also on pedagogical design, implementation quality, learner participation, teacher support, assessment methods, and institutional context.

Recent reviews have examined AI-based learning tools, personalized learning applications, and the integration of machine learning and generative AI into learning analytics (Luo et al., 2025; Peng & Li, 2025; Rodriguez-Ortiz et al., 2025). However, the literature remains dispersed across multiple technologies, educational settings, and outcome categories. Existing narrative and systematic reviews provide valuable evidence on particular applications but offer less visibility into the relationships among major themes and their development over time. A scientometric analysis is therefore needed to identify the field's publication patterns, thematic clusters, temporal evolution, and emerging research fronts.

3. MATERIAL AND METHODS

3.1 Data Source and Search Strategy

The bibliographic data were retrieved from the Web of Science Core Collection. The search period was restricted to publications from January 2015 to December 2025. The search strategy combined four groups of topic terms relating to artificial intelligence, personalized learning, academic performance, and higher education. The AI-related terms included expressions such as *artificial intelligence*, *AI-powered*, *intelligent tutoring systems*, and *adaptive learning systems*. Personalized learning terms covered *personalized learning*, *personalised learning*, *adaptive learning*, and related forms, while academic outcome terms included *academic performance*, *academic achievement*, *student performance*, *learning outcomes*, and *learning effectiveness*. Higher education terms included *higher education*, *university*, *college*, *undergraduate*, and *tertiary education*.

The search was conducted on 23 July 2026. Only English-language journal articles and review articles were considered. The original Web of Science export contained 200 unique records with full bibliographic information and cited references. During data preparation, seven records assigned a final publication year of 2026 were identified and excluded because they fell outside the predefined study period. No duplicate accession numbers were found. The final analytical sample therefore consisted of 193 records published within the 2015–2025 search window. Although the search period began in 2015, the first eligible publication in the final dataset appeared in 2017.

The bibliographic records were downloaded in plain-text format with full records and cited references to ensure compatibility with CiteSpace. The original export was retained as a backup, while the screened records were organized into annual data files for subsequent analysis. The screening process ensured consistency between the publication period, final sample, and visualized results.

3.2 CiteSpace Configuration and Analytical Procedures

CiteSpace 7.0.1 Advanced, 64-bit, was used to analyze the intellectual structure and development of the research field. The time-slicing period was set from 2015 to 2025, with one year per slice. Because no eligible records were published in 2015 or 2016, the effective visualized period began in 2017 for several network maps.

The term sources included titles, abstracts, author keywords, and Keywords Plus. Node selection was based on the g-index with the scaling factor set at k = 25. The link-retaining factor was 2.5, links per node were set at 10, the look-back period was five years, and the e value was 1.0. No pruning strategy was applied to the final networks. Cluster labels were generated using the log-likelihood ratio method because it provided distinctive labels for interpreting the thematic structure of the field.

Several complementary analyses were conducted. Annual publication counts were used to describe the growth of the literature. Country and institutional analyses identified the major geographical and organizational contributors. Keyword co-occurrence and clustering analyses were used to reveal major research hotspots, while the timeline view illustrated their temporal development. Keyword burst detection was applied to identify terms that received rapidly increasing attention during specific periods; the burstness parameter was adjusted to $\gamma = 0.5$, with a minimum duration of two years. Reference co-citation analysis was used to identify the principal intellectual foundations supporting the field.

Network structure was evaluated using the number of nodes and links, network density, modularity Q, and weighted mean silhouette S. A higher modularity value indicates clearer separation among clusters, while a higher silhouette value reflects greater internal consistency within each cluster. The quantitative indicators, cluster labels, timeline patterns, and burst intervals were interpreted together to identify established research themes and emerging directions in AI-powered personalized learning and academic performance in higher education.

4. RESULTS AND DISCUSSION

4.1 Publication Growth and Research Distribution

The final dataset contained 193 publications within the 2015–2025 search period. No eligible publications were identified in 2015 or 2016, and the first retained record appeared in 2017. Publication output remained limited between 2017 and 2019, with only one record per year. The number increased to four in 2020 and eight in 2021, followed by a temporary decline to two publications in 2022. Research activity subsequently accelerated, reaching nine publications in 2023, 39 in 2024, and 128 in 2025.

The final two years accounted for 167 publications, representing 86.5% of the total sample. In particular, publications in 2025 alone accounted for 66.3% of all records. This sharp increase indicates that AI-powered personalized learning and academic performance have developed into a rapidly expanding research area. The growth may be associated with the widespread adoption of generative AI, learning analytics, intelligent assistants, and adaptive learning platforms in higher education. However, the concentration of publications in the final two years also suggests that many research themes remain relatively new and may not yet have developed a stable empirical or theoretical foundation.

Table 1. Annual Publication Output and Leading Contributing Countries

Panel A. Annual publication output

Year	Number of publications
2017	1
2018	1
2019	1
2020	4
2021	8
2022	2
2023	9
2024	39
2025	128
Total	**193**

Panel B. Leading contributing countries

Country/region	Number of publications
People's Republic of China	47
Saudi Arabia	15
United States	15
Pakistan	12
Malaysia	12
India	11
Taiwan	10

The country collaboration network contained 36 nodes and 94 links, with a network density of 0.1492. China contributed the largest number of publications, accounting for 47 records, followed by Saudi Arabia and the United States with 15 publications each. Pakistan and Malaysia contributed 12 publications each, while India and Taiwan also occupied visible positions in the network.

The geographical distribution shows that the field has a strong Asian and Middle Eastern research presence. China's leading position reflects its growing investment in educational technology, artificial intelligence, and digital transformation in higher education. The contributions of Malaysia, Pakistan, Saudi Arabia, and the United Arab Emirates further indicate that AI-supported learning is attracting substantial attention in rapidly digitalizing education systems. At the same time, the participation of the United States, England, Spain, Germany, and Australia demonstrates that the field is internationally connected rather than concentrated within a single region.

The institutional collaboration network was comparatively small, consisting of 15 selected nodes and 28 links. Institutions visible in the network included Prince Sattam Bin Abdulaziz University, King Saud University, King Abdulaziz University, Universiti Teknologi Malaysia, Korea University, United Arab Emirates University, and Near East University. The relatively limited institutional network suggests that research remains dispersed across individual universities and project teams. Stronger inter-institutional collaboration may therefore be required to support larger datasets, comparative studies, and cross-cultural validation.

4.2 Research Hotspots and Keyword Clusters

The keyword co-occurrence network contained 201 nodes and 677 links, with a density of 0.0337. The modularity value was $Q = 0.6222$, while the weighted mean silhouette value was $S = 0.7532$. These values indicate that the network formed relatively distinct thematic clusters with acceptable internal consistency.

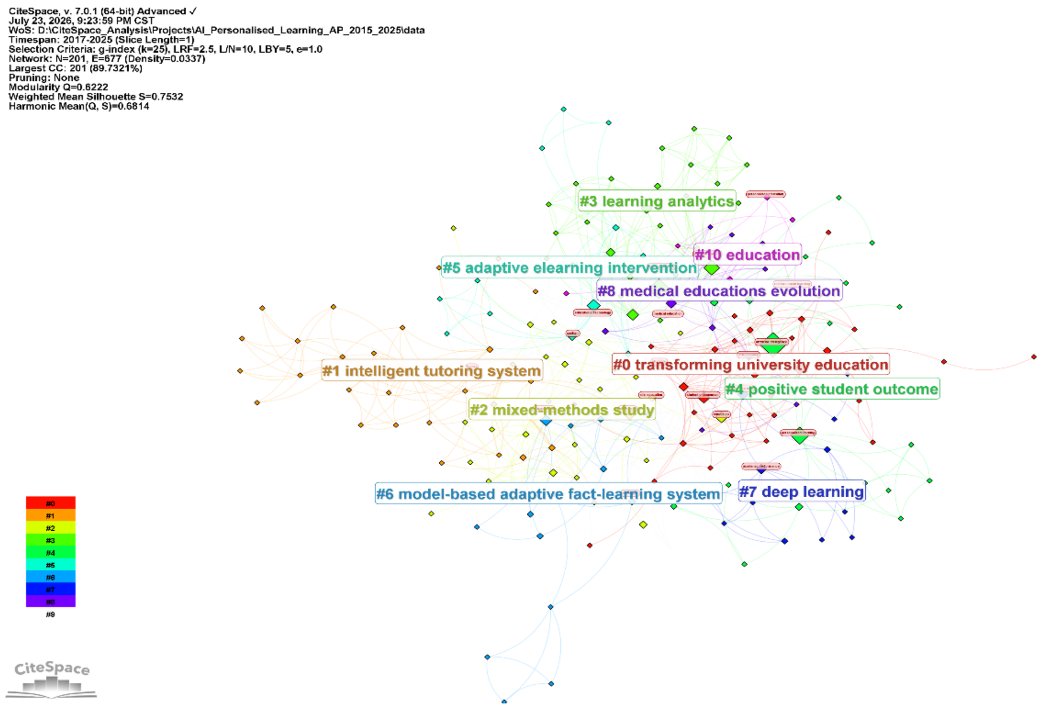

Figure 1. Keyword Co-occurrence and Cluster Network

The keyword analysis identified several major research hotspots. The largest cluster was labelled transforming university education, reflecting recent interest in the broader institutional implications of AI. This cluster included themes associated with adaptive assessment, educational transformation, systematic analysis, and the integration of AI into university teaching and learning.

The second major cluster, intelligent tutoring system, represented an earlier technological foundation of the field. It included fuzzy logic, semantic frameworks, Bayesian methods, learner modelling, and personalized recommendation. These themes correspond to the initial stage of AI-supported personalization, when researchers focused primarily on developing intelligent systems capable of selecting learning materials or responding to individual learner characteristics.

The learning analytics cluster connected machine learning, educational data, context-aware interaction, and smart learning environments. It reflects the transition from rule-based adaptation toward data-driven prediction and intervention. Learning analytics enables institutions to identify learning difficulties, predict academic risk, and provide targeted support based on students' behavioural and performance data.

The positive student outcome cluster concentrated on academic performance, engagement, attendance, retention, and related educational results. Its presence demonstrates that researchers increasingly evaluate AI systems not only according to technical accuracy but also according to whether they produce meaningful educational benefits.

Other important clusters included adaptive e-learning intervention, deep learning, mixed-methods study, and model-based adaptive fact-learning system. Together, these themes show that the field combines technical system development, predictive modelling, instructional intervention, and learner-centred evaluation.

Table 2. Major Keyword Clusters and Citation Bursts
Panel A. Major keyword clusters

Cluster	LLR label	Size	Silhouette	Mean year
#0	Transforming university education	35	0.580	2024
#1	Intelligent tutoring system	32	0.711	2020
#2	Mixed-methods study	27	0.632	2024
#3	Learning analytics	27	0.851	2022
#4	Positive student outcome	20	0.844	2023
#5	Adaptive e-learning intervention	15	0.819	2020
#6	Model-based adaptive fact-learning system	15	0.824	2023
#7	Deep learning	12	0.866	2022

Panel B. Keywords with the strongest citation bursts

Keyword	Strength	Beginning	End
Instruction	1.26	2017	2025
Intelligent tutoring system	1.51	2018	2021
Fuzzy logic	1.27	2018	2020
System	2.66	2019	2022
Adaptive e-learning	1.29	2019	2020
Individual differences	1.81	2020	2021
Adaptive learning	3.57	2021	2023
Performance	1.30	2021	2025

The reference co-citation analysis further supported these thematic findings. The largest co-citation clusters were labelled positive student outcome, adaptive assessment, and artificial intelligence, with 58, 46, and 36 references respectively. Earlier intellectual foundations were represented by clusters relating to statistical learning, machine learning, and learning analytics. A more recent cluster labelled students voice reflected increasing attention to learner perceptions, acceptance, trust, and participation.

These co-citation structures indicate that the field has developed through the interaction of three knowledge foundations. The first concerns technical methods, including statistical learning, machine learning, and deep learning. The second focuses on adaptive assessment, intelligent tutoring, and personalized intervention. The third concerns educational outcomes and learner experience. The combination of these foundations has gradually shifted the field from technology development toward broader questions of effectiveness, implementation, and educational value.

4.3 Temporal Evolution and Emerging Trends

The keyword timeline illustrates how the main themes developed between 2017 and 2025.

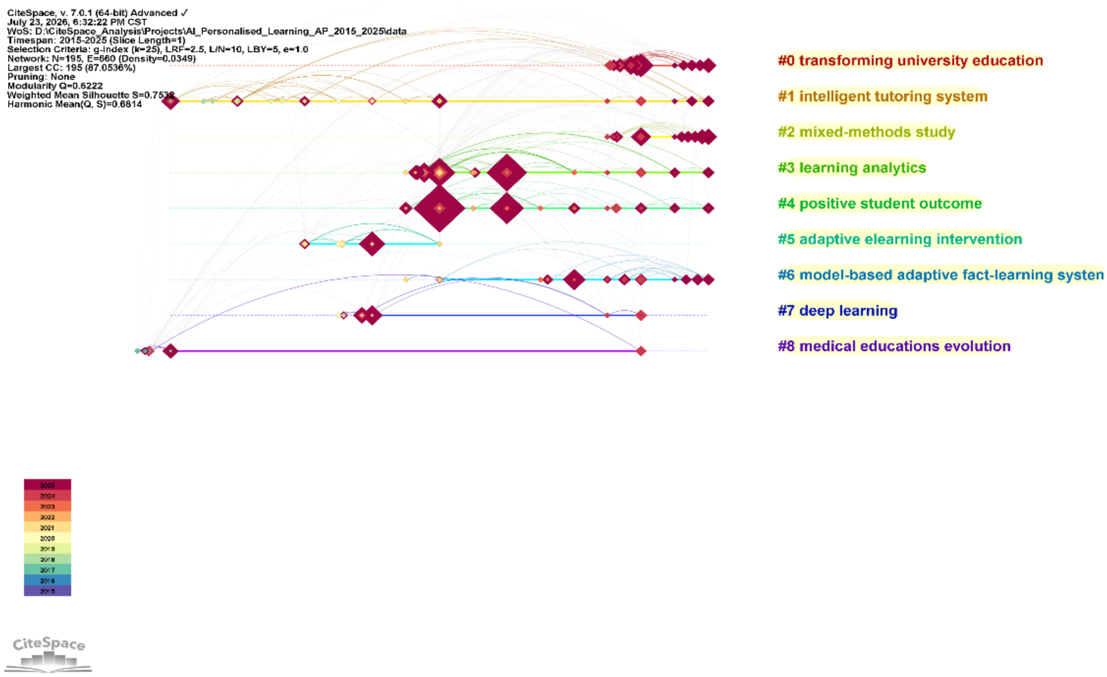

Figure 2. Timeline View of Major Research Clusters

The evolution of the field can be divided into three overlapping stages.

The first stage, approximately from 2017 to 2019, was dominated by system-centred and rule-based approaches. Important themes included intelligent tutoring systems, fuzzy logic, semantic frameworks, and adaptive e-learning. Research during this period focused on how learner characteristics could be represented and how learning content could be selected according to predefined rules or learner profiles. The citation bursts for intelligent tutoring system and fuzzy logic confirm the importance of these technical foundations.

The second stage, approximately from 2020 to 2022, was characterized by data-driven personalization. Research increasingly used learning analytics, statistical learning, machine learning, and deep learning to predict academic achievement, dropout risk, engagement, and individual differences. The burst of system between 2019 and 2022 and individual differences between 2020 and 2021 reflects this transition. The focus shifted from simply adapting instructional materials to using educational data for prediction, diagnosis, and targeted intervention.

The third stage, from approximately 2023 to 2025, reflects the emergence of generative AI, institutional transformation, and outcome-oriented evaluation. Recent clusters such as transforming university education, mixed-methods study, positive student outcome, and model-based adaptive learning show that researchers are now examining how AI affects teaching practices, student engagement, assessment, and institutional change. Generative AI has extended personalization from recommending predetermined resources to generating explanations, summaries, exercises, feedback, and conversational support in real time.

Among the eight strongest citation bursts, adaptive learning had the highest strength, at 3.57, and remained active from 2021 to 2023. This indicates that adaptive learning became a major research front during the period when institutions increasingly adopted data-driven and intelligent learning environments. The burst for performance continued from 2021 to 2025, showing that academic outcomes remain a persistent concern. The long-term burst of instruction, extending from 2017 to 2025, further indicates that personalization continues to be understood as an instructional issue rather than merely a technological one.

The combined evidence from clusters, timelines, and bursts suggests that terminology has changed more rapidly than the underlying educational problem. Although fuzzy logic and intelligent tutoring systems are no longer the most prominent emerging terms, their core objective—matching instructional support to individual learner needs—remains central. More recent concepts such as generative AI, adaptive assessment, learning analytics, and intelligent assistants represent new technical approaches to the same fundamental challenge.

4.4 Integrated Discussion and Implications

The findings show that AI-powered personalized learning has evolved from a specialized system-development field into a broader research area connecting technology, pedagogy, analytics, and student outcomes. Earlier studies concentrated on intelligent tutoring systems and rule-based adaptation, whereas more recent research emphasizes predictive analytics, generative AI, mixed-methods evaluation, and institutional transformation.

Academic performance has remained a central outcome throughout this development. The continuing burst of performance and the prominence of the positive student outcome co-citation cluster indicate sustained pressure to demonstrate educational value. However, previous studies have reported mixed results. Some research found improvements in achievement, motivation, engagement, and self-regulated learning, while other studies identified non-significant differences in course performance (Lim et al., 2023; Wei, 2023; Eltahir & Babiker, 2024). These differences suggest that AI does not improve academic performance automatically. Its effectiveness depends on instructional design, learner participation, teacher support, assessment methods, implementation duration, and institutional context.

Several emerging research gaps can be identified. First, more longitudinal and causally informative studies are needed. Many current studies are based on short-term interventions, small samples, or single institutions. Second, future research should integrate stronger educational theories rather than treating AI as an isolated technical tool. Third, privacy, algorithmic bias, academic integrity, transparency, and unequal access require greater attention. Finally, cross-institutional and cross-cultural studies are necessary because the current literature is geographically concentrated and may not be directly transferable across different education systems.

For universities, the findings imply that AI-powered personalized learning should be implemented as a socio-technical and pedagogical intervention. Effective adoption requires more than software procurement. Institutions need data governance, educator training, ethical guidelines, transparent assessment procedures, and mechanisms through which students can question or correct automated recommendations. Researchers and practitioners should therefore evaluate AI systems according to both technical performance and their contribution to meaningful, equitable, and sustainable learning outcomes.

5. CONCLUSION

This study examined the development of research on AI-powered personalized learning and academic performance in higher education through a scientometric analysis of 193 Web of Science records published between 2015 and 2025. CiteSpace was used to identify publication trends, major contributors, keyword clusters, temporal patterns, citation bursts, and the intellectual foundations of the field. The findings show that research activity expanded rapidly after 2023, with China contributing the largest number of publications and Asian and Middle Eastern countries forming an important part of the international research network.

The thematic results indicate a clear evolution from intelligent tutoring systems, fuzzy logic, and rule-based adaptation toward learning analytics, machine learning, deep learning, adaptive assessment, and generative-AI-supported personalization. Major research hotspots included transforming university education, intelligent tutoring systems, learning analytics, adaptive e-learning interventions, positive student outcomes, and deep learning. Adaptive learning produced the strongest keyword burst, while performance and instruction remained active through 2025, showing that the field continues to focus on both instructional design and measurable educational outcomes.

Overall, AI-powered personalized learning is developing from a technology-centred research area into a broader field that integrates data analytics, pedagogy, learner experience, and institutional transformation. However, rapid publication growth does not necessarily indicate mature evidence. Future studies should strengthen causal and longitudinal research designs, integrate educational theory more explicitly, and examine privacy, equity, transparency, academic integrity, and algorithmic bias. Cross-institutional and cross-cultural validation is also required to improve the generalizability of findings.

This study is limited by its reliance on a single Web of Science dataset, the concentration of publications in 2024 and 2025, and the dependence of cluster labels on algorithmic interpretation. Nevertheless, it provides a concise overview of the knowledge structure, research hotspots, and emerging trends in this rapidly developing field and offers a foundation for future research and institutional decision-making.

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