International Journal of Innovative Research and Scientific Studies, 8(6) 2025, pages: 1950-1963

IJIRSS International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

A systematic review (2010–2024) of smart textbooks and intelligent tutoring systems: Models, methods, subjects, and geographies

Marat Zhumashev[1], Alibek Barlybayev[1,2*], Aliya Kintonova[1], Amanbek Sabitov[1], Saule Kudubayeva[1]

[1]*Faculty of Information Technology, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan.*
[2]*Faculty of Information Technology and Engineering, Astana International University, Astana, Kazakhstan.*

Corresponding author: Alibek Barlybayev (*Email: frank-ab@mail.ru*)

Abstract

To synthesize peer-reviewed studies from 2010–2024 on smart textbooks and intelligent tutoring systems, mapping the evolution of models and methods, subject-area coverage, and geographic trends, and cataloging reported advantages and limitations. A PRIS-MA-guided systematic review was conducted across Google Scholar, Scopus, and Web of Science using search terms centered on "smart/intelligent textbook" and "intelli-gent/smart tutor"; from 233 records, 26 studies met inclusion criteria and were coded by year, subject, country, models, and methods. Research activity was modest in 2010–2014, increased from 2015, and peaked in 2021–2022; General Education (n=16) and Program-ming (n=7) dominated subject coverage, while Mathematics, Chemistry, Pedagogy, Eng-lish, and Computer Science appeared infrequently (1–3 occurrences). Publications were concentrated in Asia—India (n=9), China (n=8), Japan (n=3)—with contributions from the United States (n=3) and select European countries. Student Model and Expert Model were the most common abstractions (3 uses each); adaptive learning systems (n=9) and knowledge-graph construction (n=6) were the leading methods. Reported benefits includ-ed individualized pacing and early difficulty detection, whereas recurrent concerns were methodological heterogeneity (12/26) and privacy/ethics (10/26). AI-enhanced education is shifting from heuristic sequencing toward semantically grounded, data-driven orchestra-tion that integrates learner and expert models with adaptive engines and knowledge graphs. To translate technical promise into durable and equitable learning gains, future implementations should broaden subject coverage, standardize reporting to enable me-ta-analysis, rigorously evaluate fairness and privacy, and embed explainable, teach-er-centered workflows across diverse contexts.

Keywords: Adaptive learning, Artificial intelligence in education, Intelligent tutoring system, Knowledge graphs, Learning analytics, Smart textbook, Systematic review.

DOI: 10.53894/ijirss.v8i6.10048
Funding: This research has been funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant Number: AP26195651).
Informed Consent Statement: Informed consent was obtained from all subjects involved in the study..
History: Received: 1 August 2025 / **Revised:** 2 September 2025 / **Accepted:** 4 September 2025 / **Published:** 19 September 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.
Publisher: Innovative Research Publishing.

1. Introduction

The 21st century marks an era of rapid technological advancement and digital transformation that is fundamentally reshaping the education system. The primary driving force behind these changes is artificial intelligence (AI) technologies. AI has transformed educational content, teaching methodologies, and the forms of interaction between learners and educators, opening new opportunities. Over the past decade, AI-powered systems have been increasingly applied in the field of education [1, 2].

One of the key advantages of AI tools in education lies in their ability to personalize and adapt learning while enabling data-driven decision-making. In particular, adaptive learning systems can analyze each student's learning patterns and propose individualized learning trajectories [3]. Such platforms automatically adjust content according to the learner's academic performance, engagement level, and errors [4, 5]. Compared to the traditional sequential structure of education, this approach significantly enhances learning efficiency [6].

Since 2020, the COVID-19 pandemic has compelled the widespread adoption of online learning platforms in education. During this period, digital environments and AI-based solutions became increasingly relevant [7]. E-learning systems rapidly evolved, incorporating new features such as monitoring academic progress, analyzing motivation, and predicting learning outcomes [8]. AI tools integrated into learning platforms provided educators with real-time analytical insights, enabling them to adapt the learning process [9].

AI is actively applied not only in technical disciplines but also in the humanities and natural sciences. Notable examples can be found in subjects such as English language, mathematics, biology, geography, and cybersecurity [10, 11]. For example, adaptive systems for learning English (e.g., ChatClass) automatically assess students' proficiency levels and offer appropriate tasks to develop language skills [11, 12]. In geography, adaptive cartographic systems and interactive content help enhance students' spatial thinking skills [2].

AI systems in education rely on technologies such as neural networks, knowledge graphs, cognitive models, natural language processing (NLP), computer vision (CV), emotion recognition, and big data analytics [9, 13]. For example, adaptive learning systems with emotion recognition can detect students' facial expressions through cameras and adjust the difficulty of tasks or teaching style accordingly [8, 9].

Over the last fifteen years, the algorithms and models used have evolved significantly. While classical methods such as decision trees, SVM, and k-NN dominated the early stages, later years saw a shift toward deep learning models such as LSTM, CNN, RNN, Transformer, and GNN. For instance, recurrent neural networks (RNN) and long short-term memory (LSTM) models have proven effective in analyzing learners' trajectories over time [14, 15].

Research indicates that AI tools not only automate teaching but also provide opportunities for predicting academic outcomes, monitoring performance, and identifying learning difficulties in advance [1, 5, 16]. This is especially valuable for students with special educational needs. For example, intelligent learning systems for students with dyslexia can adapt texts and adjust learning strategies.

Enhancing teaching effectiveness through AI technologies is crucial for both educational policy and practice. However, most studies focus on a specific subject or technological tool. Conducting a systematic review to identify in which subjects AI is actively applied, with which models and algorithms, in which countries, by which research methods, and in what developmental directions, is an urgent task for the scientific community [1, 10].

In this study, over 200 scientific articles published between 2010 and 2024 were reviewed, of which 26 were analyzed in greater detail. The evolution of AI models and methods, their frequency of application by subject area, algorithmic foundations, geographic distribution, and research activity over time were examined in depth. Additionally, the evolution of AI models was systematically presented in a dedicated table.

The aim of this study is to systematically analyze the application of artificial intelligence technologies in education between 2010 and 2024, to identify the evolution of the models, methods, and algorithms used, and to evaluate AI's impact on the education sector by highlighting subject-specific and geographic trends.

Research Hypothesis: If artificial intelligence technologies are systematically integrated into education, they will not only improve learning outcomes but also enable the personalization and adaptation of the learning process. This process will be implemented through various models and methods depending on subject-specific features and country-specific contexts.

1.1. Research Questions

1. What core models and methods of artificial intelligence have been applied in education between 2010 and 2024?
2. In which subjects are AI technologies most frequently applied, and what are their specific applications?
3. How have AI technologies been implemented in education across different countries?
4. Which AI models have evolved to become dominant over time?

2. Evolution of Learning Models

Over the past fourteen years (2010–2024), the structure and content of learning models applied in the field of education have undergone significant changes. These transformations are closely linked to the advancement of educational technologies, the increasing personalization of teaching approaches, and the integration of artificial intelligence tools.

The analysis of the reviewed scholarly literature revealed the most frequently applied models, including: Expert Model (EM) [17], Student Model (SM) [17], Revised Bloom's Taxonomy (RBT) [18] Felder–Silverman Learning Style Model (FSLSM) [18] natural language processing models (NLP) [11] TIP model (3D visualization) [19] virtual reality environment (VR) [19] and Teaching Model (TM) [20].

Classical pedagogical models (e.g., RBT, EM, FSLSM) dominated from 2010 to 2015. During this period, structuring learning content, conducting expert-based assessments, and accounting for students' learning styles played a key role. From 2015 onwards, there was a noticeable shift toward models focusing on personalization, visualization, and the integration of digital tools. In this regard, approaches based on the student model (SM), 3D visualization (TIP), and adaptive learning systems gained wide adoption.

Since 2020, AI-powered NLP models and transformer-based language architectures (such as BERT, GPT, and others) have been actively integrated into the learning process. Additionally, virtual and augmented reality technologies have enabled the creation of immersive learning environments, with VR platforms being widely applied in education.

Table 1 presents a systematized overview of each model's year of introduction, period of application, and evolutionary characteristics.

Table 1.
Evolution of Learning Models.

Model Name	Year of Introduction	Originators	Evolutionary Characteristics
EM	1970s–1980s	Used in AI-based tutoring systems	Applied in modeling expert perspectives and assessing teaching quality.
SM	1970s–1980s	Early work in Intelligent Tutoring Systems [17, 21]	Used for modeling students' knowledge levels and adapting learning trajectories.
TM	1972	[6, 22]	Traditional teaching methods adapted to the context of digital learning.
FSLSM	1988	[18, 23]	A model describing learning preferences across four dimensions (active–reflective, sensing–intuitive, visual–verbal, sequential–global); widely applied in engineering and STEM education.
RBT	2001	(Former student of Bloom) [18, 24]	Extensively applied in structuring learning objectives within digital education systems.
3D visualization	2010	Does not have a single universally accepted origin or author.	Demonstrated effectiveness in STEM disciplines through interactive visual content.
VR	2012	NASA & research institutions began using VR for training in the 1990s Widespread educational use grew after 2012 (Oculus, Google Cardboard) [19]	Fostered immersive learning experiences and gained wide adoption through platform-based implementation.
NLP	~2013	Word2Vec (2013) seq2seq models (2014) Attention mechanism (2015) Transformer (2017) BERT (2018), GPT series (2018–2023)	Applied in modeling expert perspectives and assessing teaching quality.

This dynamic evolution of models demonstrates that education is undergoing a technological transformation. In recent years, the influence of artificial intelligence, adaptive systems, and immersive technologies (VR, AR) has particularly increased. These directions are shaping a new educational paradigm aimed at delivering personalized, learner-centered, and interactive learning experiences tailored to the needs of students.

3. Materials and Methods

3.1. Reearch Process

The methodology developed and used in this study is presented in Figure 1. The methodology for reviewing the literature on AI technologies for improving the educational process consists of the following steps (process names are taken from Figure 1):

1. Research questions (Q) development. Based on the research objectives, research questions are formulated, the answers to which will be sought during the literature review. They determine the volume of data to be collected and the analysis of the results.

2. Search query development. Define database queries to retrieve publications on smart/digital textbooks and intelligent tutoring systems that apply AI/ML to personalization, feedback, and learning analytics.

3. Bibliographic databases source selection. Selection of databases from available ones, which will be used in the review.

4. PRISMA. Implementation of the search and selection of publications according to the PRISMA guidelines [25]. This step includes typical activities: searching for publications, deduplication of search results and application of inclusion and exclusion criteria.

5. Study execution. This stage includes analysis of the content of publications selected in the previous stage. The analysis is carried out using various sets of classifiers corresponding to the content of Q. The result is a database of publications assigned to various classifiers.

6. Data extraction. Analysis of the database created in stage 5.

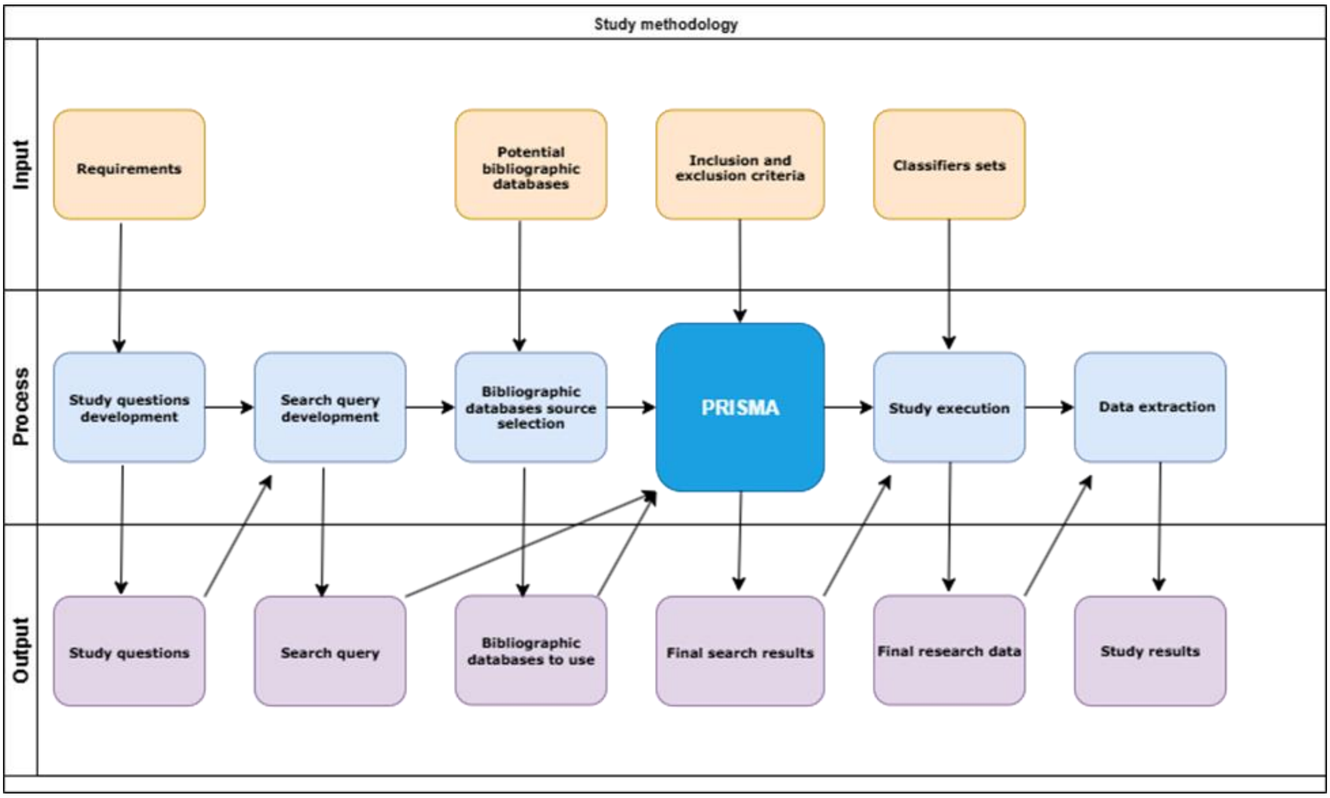

Figure 1.
This is a figure. Scemes follow the same formatting.

Based on the hypotheses defined in the Introduction chapter, the following research questions can be formulated:

Q1. To what extent has the application of artificial intelligence technologies in education developed between 2010 and 2024?

Q2. What key themes and directions have been identified in studies on the use of artificial intelligence in teaching?

Q3. What models and methods have been employed in applying artificial intelligence technologies in education, and how have they been implemented across different countries?

Q4. What outcomes have resulted from integrating artificial intelligence into the educational process, and what advantages and limitations of these technologies have been identified?

Keywords related to the development of intelligent educational systems were selected (Table 2). The final search query was structured as follows: TITLE-ABS-KEY: ("smart textbook" OR "intelligent textbook" OR "digital textbook") AND ("intelligent tutoring system" OR "smart tutor" OR "intellectual tutor") AND ("artificial intelligence" OR "AI" OR "machine learning")

This structure ensured broad coverage of the search scope and included studies focused on AI-enhanced learning tools. The main emphasis was placed on creating a personalized, interactive, and intelligent learning environment tailored to the needs of learners. Such systems allow real-time monitoring of students' learning processes, provide feedback, and adapt educational content accordingly.

Table 2.
Evolution of Learning Models.

Word	Reasons
Smart textbook, intelligent textbook	Represents a new generation of digital textbooks based on artificial intelligence.
Intelligent tutoring system, smart tutor	Core technologies that provide learners with personalized instruction and feedback.
Artificial intelligence (AI)	Key technologies enabling adaptive learning and intelligent interaction.
Machine learning	An area of AI applied in modeling learner behavior and personalizing content.

During the literature review, leading academic databases such as Google Scholar, Scopus, and Web of Science were utilized. These platforms contain the most significant scholarly studies related to smart learning systems. The selected research works were grouped into the following categories:

Set 1. Smart textbook architecture, integration of multimedia elements, and content modularization.

Set 2. Personalization through artificial intelligence, learner analytics, and adaptive content delivery.

Set 3. Intelligent tutoring systems, dialogue-based models, and virtual tutors.

Set 4. Application domains: schools, higher education institutions, and online learning platforms.

Set 5. Research methodologies: experimental studies, user testing, and learning analytics.

Set 6. Applied AI methods: natural language processing (NLP), knowledge graphs, and neural networks.

Set 7. Research objectives: increasing student engagement, fostering self-directed learning, and improving learning efficiency.

Set 8. Outcomes: adaptive learning content, intelligent feedback, learning process monitoring, and personalized learning trajectories.

3.2. Papers selection

To conduct the systematic literature review, the study followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [25] applying a precise and rigorous methodology for comprehensive coverage and analysis of the literature. The search was carried out in January 2025 and included three leading multidisciplinary academic databases: Google Scholar, Scopus, and Web of Science. The search was performed using the keywords *"Developing smart textbook"*, *"Intelligent tutoring system"*, *"intellectual textbook"*, *"smart textbook"*, *"intellectual tutor"*, and *"smart tutor"*, as illustrated in Figure 2.

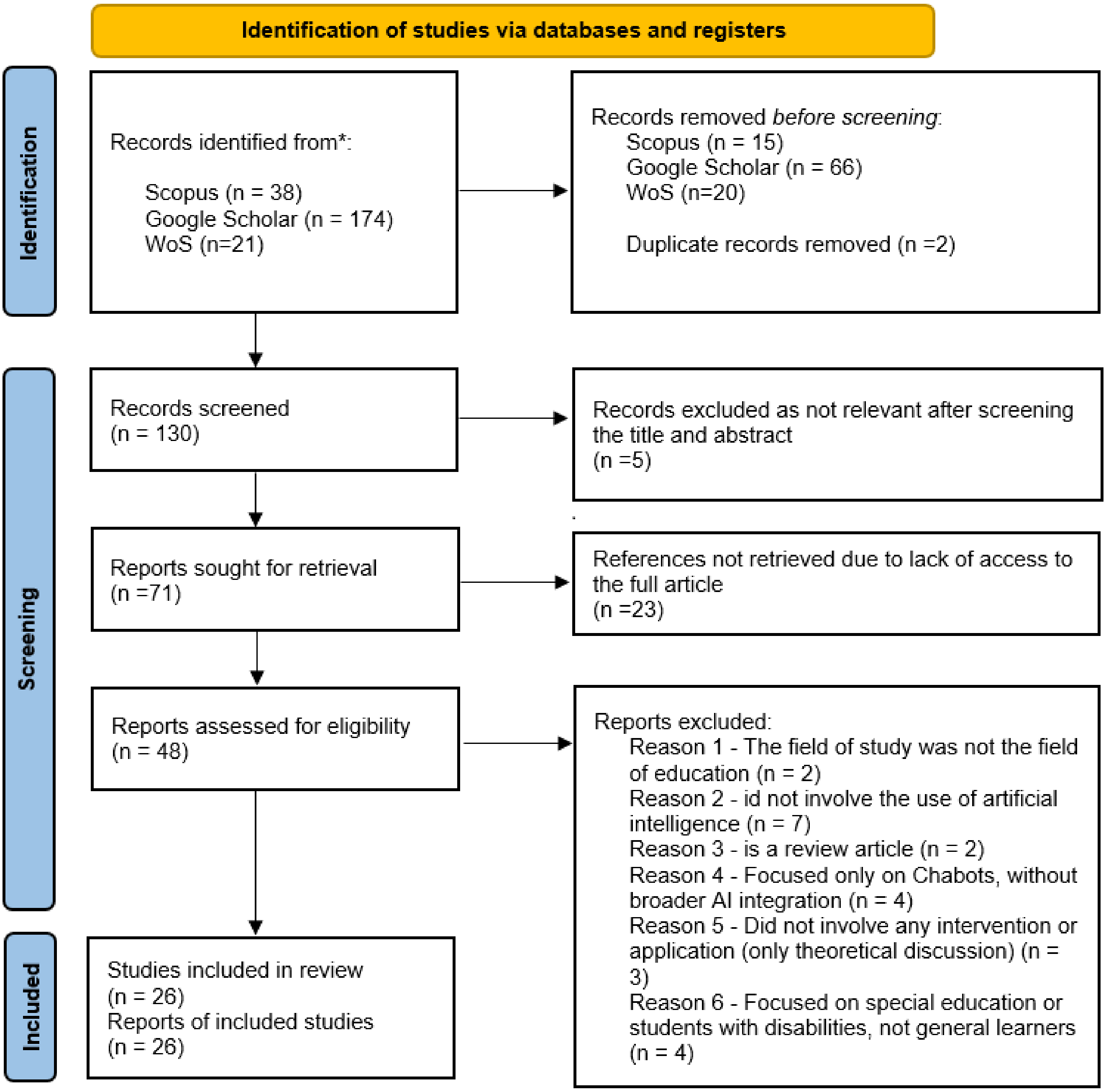

Figure 2.
PRISMA diagram of data collection for the literature review.

At the initial stage, a broad search conducted across these academic databases identified a total of 233 publications within the period from 2010 to 2024, as presented in Figure 3. Specifically, 38 articles were retrieved from the *Scopus* database, 174 from *Google Scholar*, and 21 from the *Web of Science* database.

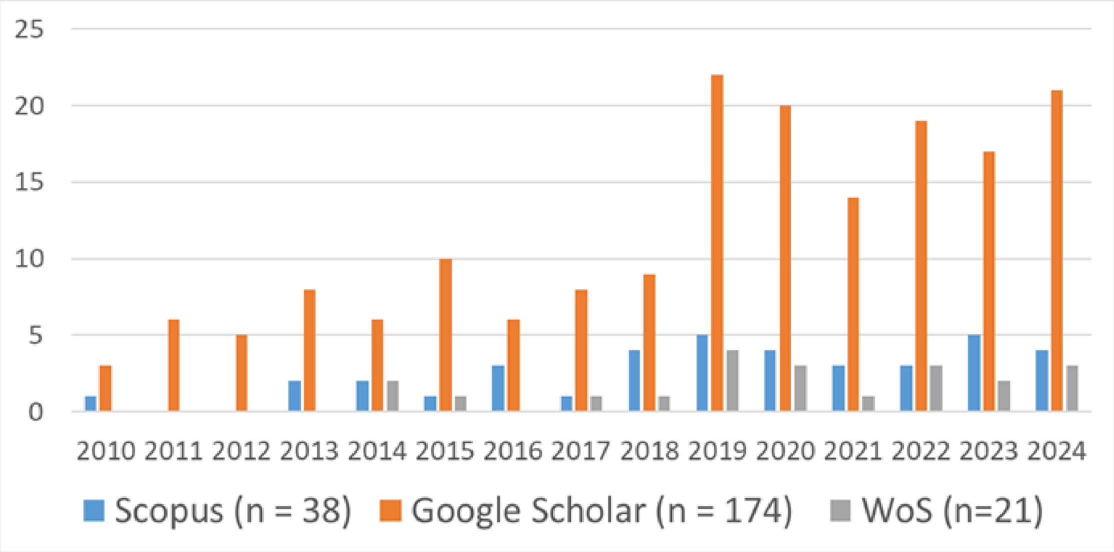

Figure 3.
Quantitative analysis and distribution of publications addressing Smart-tutoring systems issues.

To refine the initial dataset, duplicate records were first removed. Subsequently, selection criteria were applied to include only articles containing the keywords “Developing smart textbook, Intelligent tutoring system, intellectual textbook, smart textbook, intellectual tutor, smart tutor.” After the first filtering stage, the number of articles was reduced to 130. At this stage, only full-text studies written in English and published in peer-reviewed journals or conference proceedings were considered.

In the next stage, titles and abstracts were screened, resulting in the exclusion of 59 articles that did not meet the research objectives or were unrelated to the topic. As a result, 71 articles remained. Among these, 23 articles were excluded due to the lack of full-text access. The remaining 48 articles were analyzed based on their full-text content. As a result, 22 studies were excluded because they did not meet the research objectives. Specifically, two articles addressed topics unrelated to education, seven studies did not involve the application of artificial intelligence technologies, two papers were review-type works without original research results, four studies focused exclusively on chatbots without addressing the broader integration of artificial intelligence, three articles presented only theoretical considerations without practical implementation or intervention, and four studies targeted special education or students with disabilities, which did not align with the general learner focus of this research.

It is noteworthy that the keywords were considered valid regardless of their position in the document (including within the references section), which also contributed to the exclusion of certain studies. Consequently, only 26 articles fully met the inclusion criteria and were selected for this systematic literature review. The PRISMA diagram (Figure 2) illustrates the entire selection process and demonstrates the systematic and rigorous methodology used to identify 26 high-quality studies from the initial dataset.

4. Results

Figure 4 illustrates the publication dynamics of scientific articles on the application of artificial intelligence in the educational process from 2010 to 2024. The horizontal axis represents the publication years, while the vertical axis shows the number of published articles. The dots on the diagram indicate the number of publications for each specific year, and the connecting line depicts the overall trend.

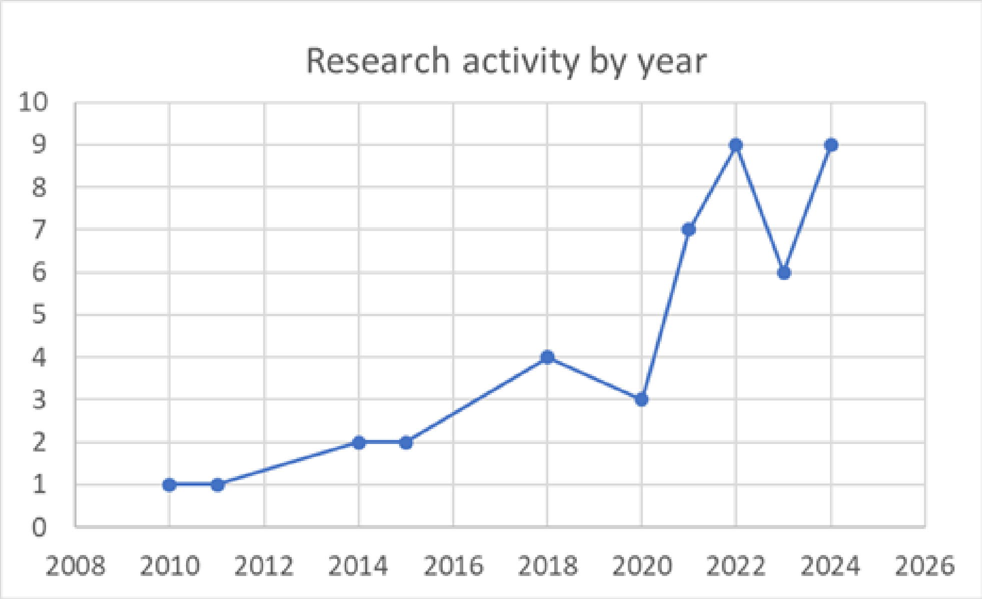

Figure 4.
Research activity by year.

According to the data presented in Figure 4, publication activity remained at a low level between 2010 and 2014, with only one to two articles published annually. Starting from 2015, a gradual increase in publications was observed, reaching four articles in 2018. Although a slight decline was recorded in 2020, a notable surge occurred from 2021 onwards, with the number of publications reaching nine in both 2021 and 2022. In 2023, the figure decreased slightly to six articles; however, in 2024, it rose again to the highest level. This trend clearly indicates a significant growth in scientific interest in the application of artificial intelligence in the field of education in recent years [2, 15].

Annual publication counts showed a significant monotonic upward trend (Mann–Kendall $\tau = 0.529$, one-sided $p = 0.0042$), with a Sen's slope of 0.545 publications per year. A log-linear Poisson regression indicated a 26.5% year-on-year increase (rate ratio, RR = 1.265, 95% CI 1.157–1.383; $\beta = 0.2351$, $p < 0.0001$). Model diagnostics suggested mild overdispersion (Pearson $\chi^2/df = 1.21$), so standard errors were retained. A negative-binomial GLM specification yielded a comparable effect (RR = 1.241, 95% CI 1.060–1.453, $p = 0.0073$), corroborating the increasing trend.

Figure 5 illustrates the frequency distribution of the subjects examined in the study. The horizontal bars represent how many times each subject was encountered in the analyzed publications. The list of subjects ranges from pedagogy to general education.

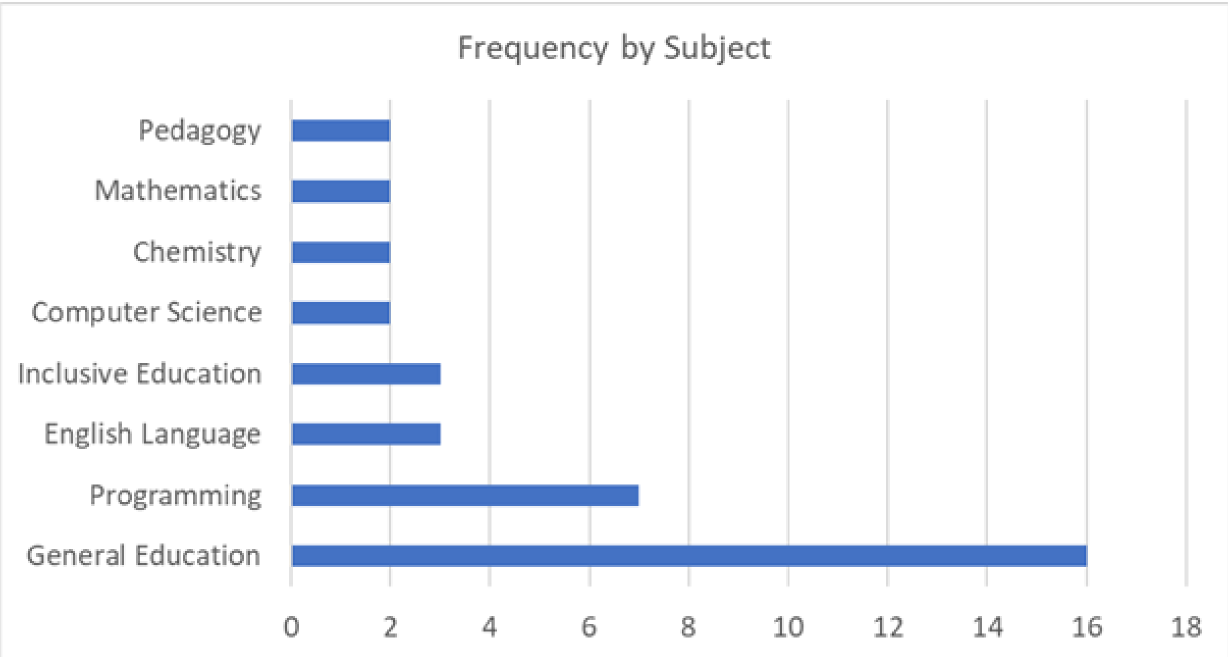

Figure 5.
Frequency by Subject.

According to the data presented in Figure 5, the most frequent subject is General Education (16 occurrences), followed by Programming (7 occurrences) in second place. The frequency for other subjects is lower: Inclusive Education – 3 occurrences, English Language – 2 occurrences, and Pedagogy, Mathematics, Chemistry, and Computer Science – each appearing only 1–2 times. These findings indicate that in the field of artificial intelligence applications, general education and programming occupy leading positions, while other subjects are less frequently researched [17, 26].

Figure 6 Illustrates the distribution of published articles by country between 2010 and 2024. The horizontal axis represents the names of countries, while the vertical axis indicates the number of published articles. The bars in the diagram reflect each country's contribution to the overall body of scientific publications on the research topic.

In total, 48 articles were selected for analysis. At the initial stage, it was assumed that 22 of them did not fully meet the research criteria. However, a more detailed examination revealed that these articles were indirectly relevant to the topic of applying artificial intelligence in education. Therefore, in order to ensure data completeness and provide a more comprehensive overview of the field, all 48 articles were included in the final analysis.

This decision allowed for greater representativeness of the research outcomes. By incorporating all available works from different countries, the study provides a more holistic picture of global research activity in the area of AI in education. Consequently, the data presented in Figure 6 are based on a broad and inclusive analysis of the international scientific literature.

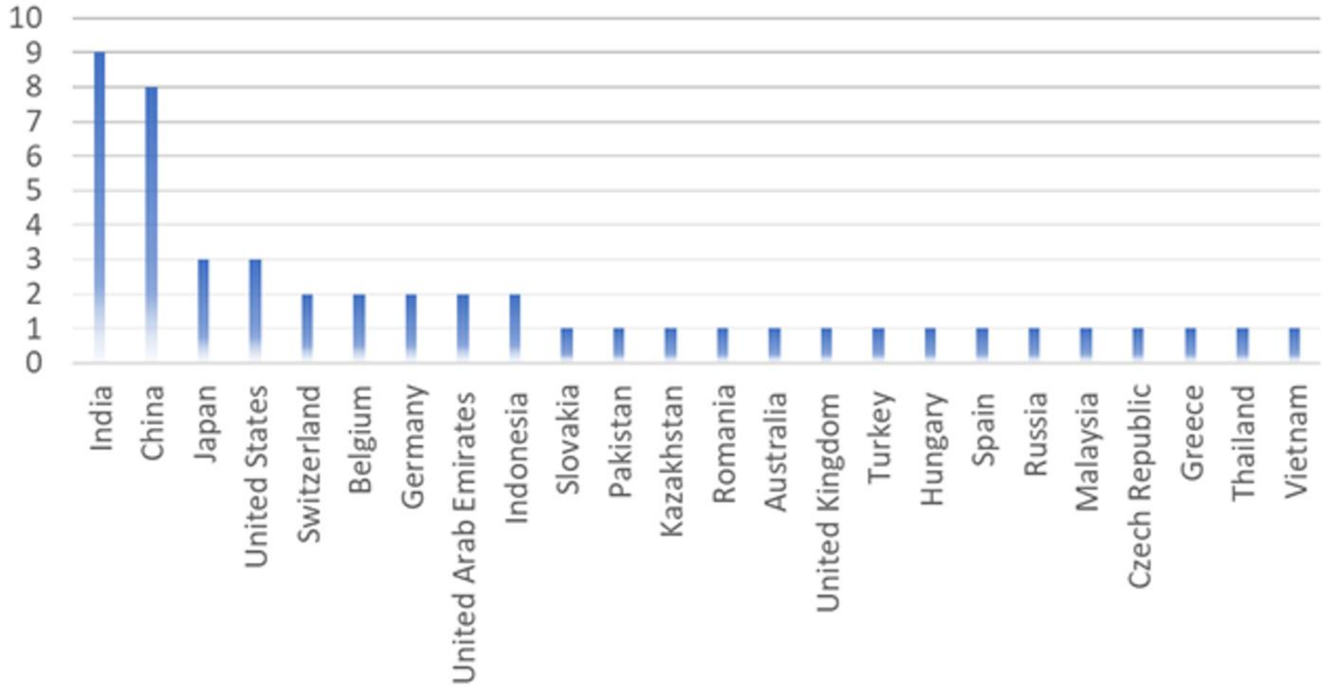

Figure 6.
Number of Articles by Country.

The results of the diagram indicate that the largest number of scientific articles on the application of artificial intelligence in education were published in India (9 articles) and China (8 articles). These countries have paid significant attention to the digitalization of education and the integration of AI technologies over the past decade. Japan and the United States follow, each contributing 3 articles. In these countries, the adoption of innovative technologies in education, particularly adaptive learning systems and intelligent tutoring platforms, has gained substantial support. Countries such as Switzerland, Belgium, Germany, and the United Arab Emirates have also contributed several studies to the field, drawing the attention of the international academic community. Other countries, including Kazakhstan, Russia, Turkey, Spain, Malaysia, the Czech Republic, Greece, Vietnam, and others, have published a smaller number of articles (1–2), yet their contributions remain significant. In most cases, these studies are focused on specific subject areas, such as language learning, STEM, or online education [12, 27].

Geographic output showed modest concentration across countries. The Gini coefficient was 0.398, indicating some inequality in the distribution of publications. The Herfindahl–Hirschman Index (HHI) was 0.086, equivalent to ~11.6 equally prolific countries (EN = 1/HHI), and the normalized HHI (NHHI) was 0.046 after adjusting for the number of active countries. By conventional HHI heuristics, this level is unconcentrated (HHI < 0.15 on the 0–1 scale), suggesting a relatively diffuse international landscape with mild dominance by a few contributors.

Figure 7 illustrates the geographical distribution of scientific articles on the application of artificial intelligence in education published between 2010 and 2024. The color scale on the map represents the number of publications: yellow and lighter shades indicate higher research activity, whereas dark blue and purple shades denote lower activity. The geographical visualization allows for a comparative assessment of countries' contributions to the field.

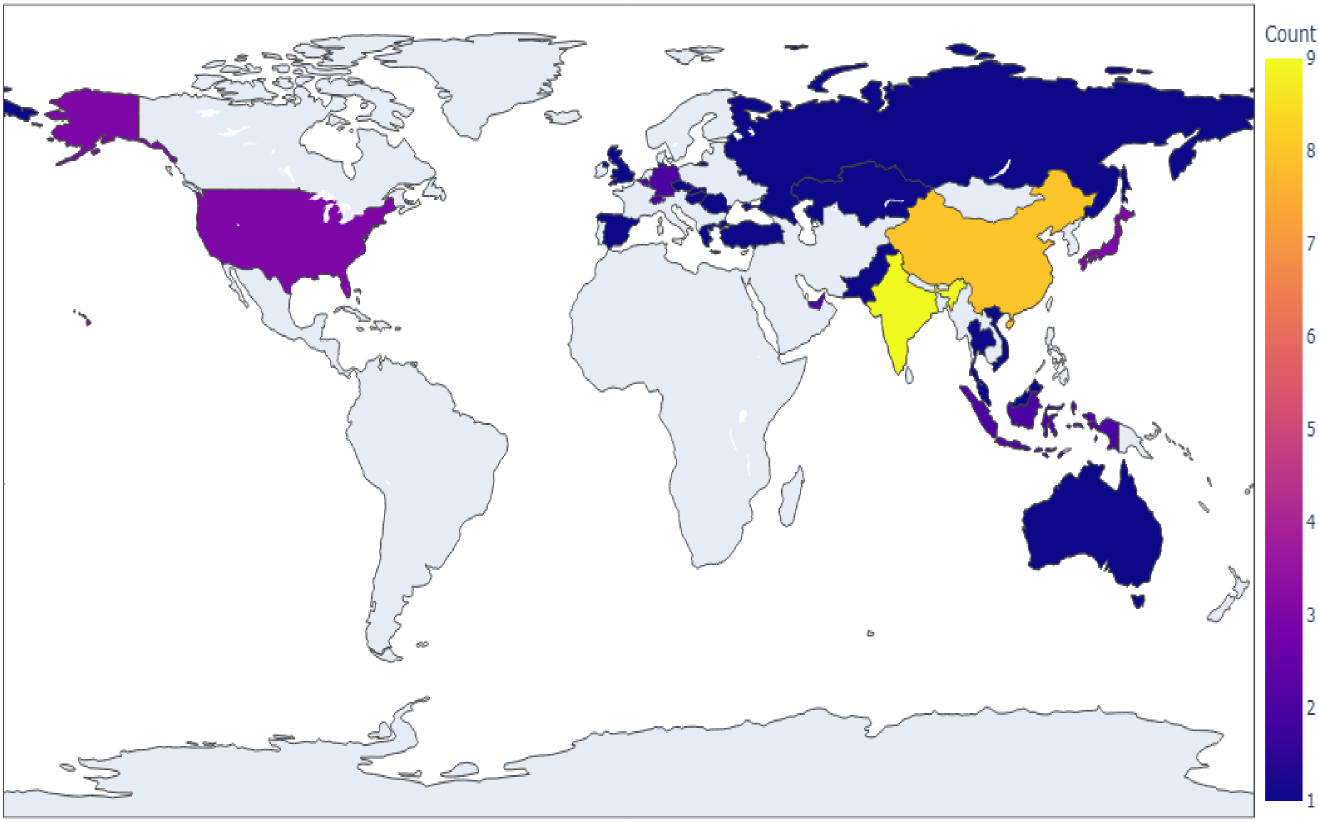

Figure 7.
Publications by Country (2010–2024).

Overall, the topic of artificial intelligence in education has exhibited a broad geographical distribution during the period 2010–2024. The leadership demonstrated by India and China can be explained by their national strategies aimed at technologically modernizing their educational systems. Specifically, Ministry of Education [28] emphasizes the integration of disruptive technologies such as artificial intelligence into the education process [29] while State Council of the People's Republic of China [30] outlines a high-level blueprint for advancing "intelligent education" through a phased, nationwide strategy. Moreover, publications from European nations and countries like Kazakhstan underscore the importance of regionally focused scientific initiatives.

These findings reveal that while countries across the globe are showing significant interest in the application of AI in education, certain states clearly dominate publication activity. Therefore, future research should focus on enhancing international collaboration and bolstering research efforts in underrepresented regions.

Figure 8 illustrates the frequency of use of the main models applied in scientific articles published between 2010 and 2024. The horizontal axis represents the names of the models, while the vertical axis shows the number of times they were used. The chart highlights how frequently various pedagogical, technological, and artificial intelligence-based models have been utilized in research studies.

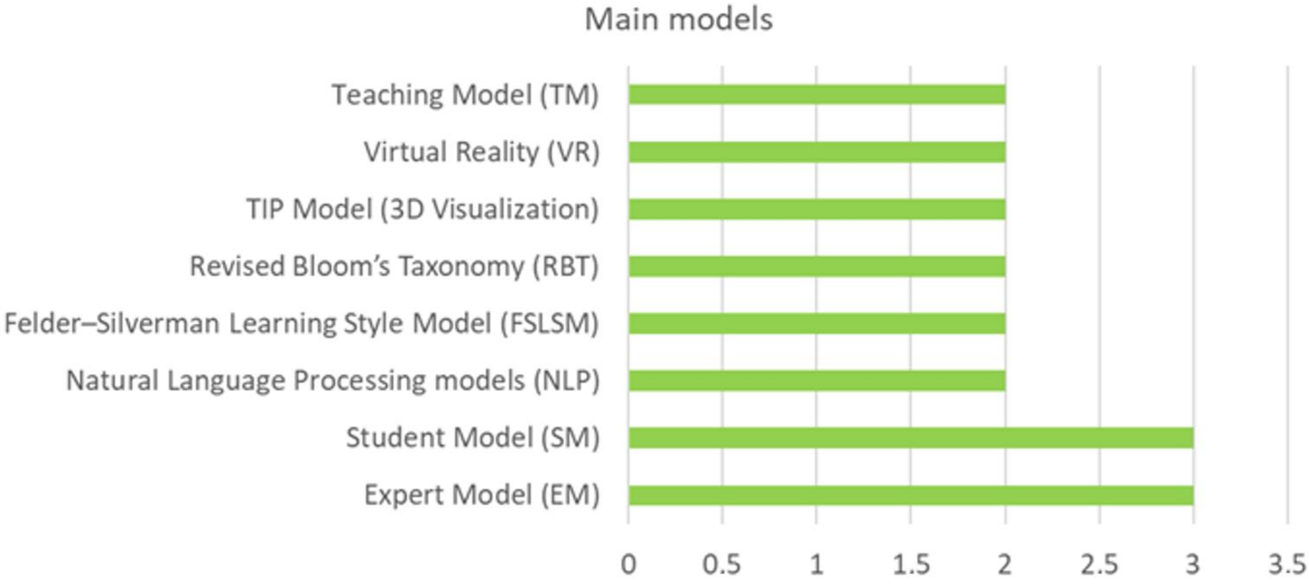

Figure 8.
Main models.

According to the data in Figure 8, the most frequently used models are the Student Model (SM) and the Expert Model (EM), each appearing 3 times. The remaining models — Teaching Model (TM), Virtual Reality (VR), TIP Model, Revised Bloom's Taxonomy (RBT), Felder–Silverman Learning Style Model (FSLSM), and Natural Language Processing models (NLP) — are each used 2 times. These results indicate that systems based on the student and expert models are predominantly used in research, while the usage frequency of other models remains at the same level [3, 5].

Figure 9 illustrates the Top 10 most frequently used models and methods found in scientific articles published between 2010 and 2024. The horizontal bars indicate how often each method has been applied. The diagram includes methods such as Evoking-hooks, Scene Database Module, Machine Learning, Learning Analytics, Big Data Analytics, Data Scraping, Blended Learning, Graph Knowledge Construction, Gamification (Emotion Analysis), and Adaptive Learning Systems.

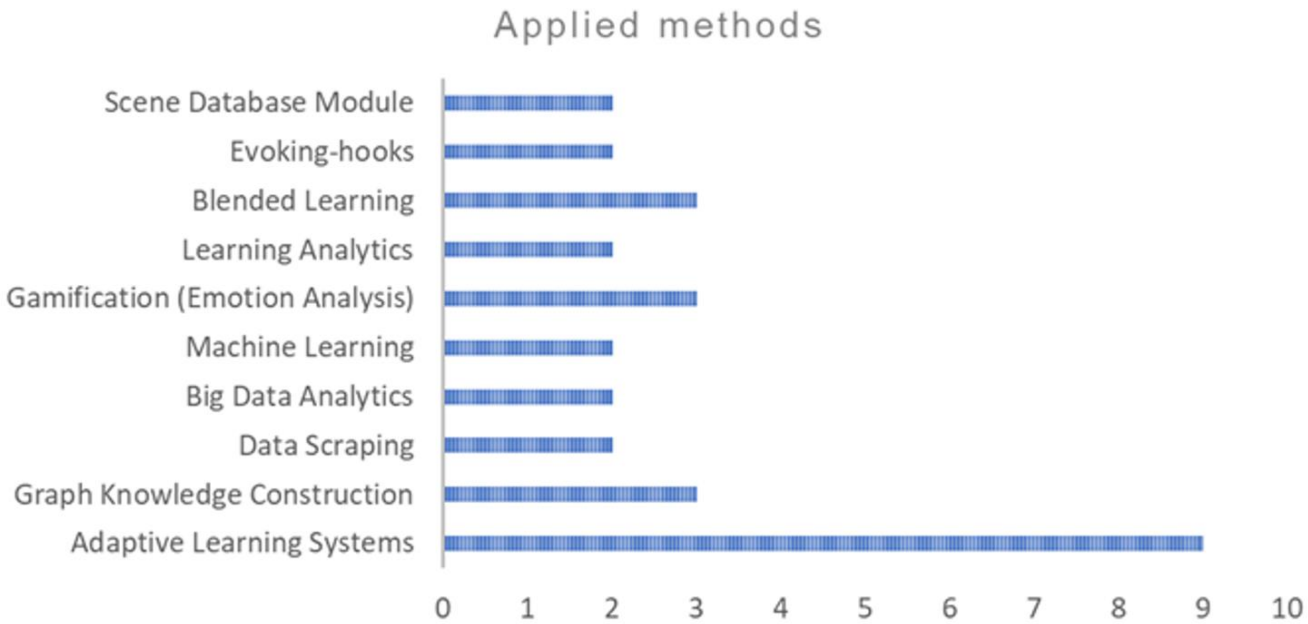

Figure 9.
Applied Methods.

According to the diagram results (Figure 9), the most frequently used method during the analyzed period was adaptive learning systems (9 occurrences). This was followed by knowledge graph construction (6 occurrences) and blended learning (3 occurrences). Machine Learning, Learning Analytics, Big Data Analytics, data scraping, and certain specialized modules (Evoking-hooks, Scene Database Module) each appeared with the same frequency—2 occurrences. These results indicate that in recent years, research has shown a strong focus on personalized, adaptive learning systems and knowledge graph–based approaches, while more traditional or less frequently applied methods remain relatively uncommon [7, 29].

5. Discussion

This systematic review synthesized 26 studies (from an initial pool of 233 publications) on the application of artificial intelligence in education between 2010 and 2024 and revealed four salient trends. First, research activity has accelerated markedly since 2015, with pronounced surges in 2021–2022, indicating a maturing and expanding research ecosystem (Fig. 4). The temporal analysis shows a transition from early, lower-frequency activity (2010–2014) to sustained growth after 2015, peaking post-2020. This pattern aligns with the rapid maturation of deep learning and the pandemic-driven expansion of digital platforms, which collectively lowered the barrier to AI deployment in classrooms and at scale. Second, the most frequently targeted domains are General Education and Programming, while subject-specific deployments in mathematics, chemistry, pedagogy, English, and computer science appear comparatively underexplored (Figure 5). Personalization and adaptivity emerge as the central themes. Adaptive systems that tailor trajectories based on learner performance, engagement, and errors are repeatedly emphasized, as are analytics for monitoring progress, diagnosing difficulties, and forecasting outcomes. The growing presence of VR/AR and 3D visualization underscores a parallel trend toward immersive, experiential learning. Third, geographically, publication output is concentrated in Asia, particularly India and China, followed by the United States and several European countries (Figure 6). The persistence of Student and Expert Models indicates that explicit representations of learner state and expert knowledge remain foundational, even as newer modalities (Transformers, knowledge graphs, emotion recognition) are layered on top. Regionally, the center of gravity in publication output lies in Asia, suggesting strong policy and infrastructural emphasis on AI-enabled education within those contexts. This concentration, however, raises questions about generalizability to underrepresented regions. Fourth, at the model level, Student and Expert Models remain the most cited pedagogical/AI abstractions, whereas adaptive learning systems and knowledge-graph–based methods dominate at the methods level, reflecting the field's pivot toward personalization and structured semantic representations (Figures 8–9). Reported benefits span improved efficiency, individualized pacing, and earlier detection of learning difficulties, including support for learners with special educational needs.

The temporal analysis indicates a clear and statistically significant acceleration of scholarship over 2010–2024. The Mann–Kendall test shows a moderate positive monotonic association between year and publication counts ($\tau = 0.529$, one-sided $p = 0.0042$), and Sen's slope of 0.545 papers/year suggests a steady absolute increase. Complementing this nonparametric evidence, the Poisson model yields a multiplicative interpretation: an estimated 26.5% year-on-year rise (RR = 1.265, 95% CI 1.157–1.383; $\beta = 0.2351$, $p < 0.0001$). Taken together, these results imply rapid compounding, roughly a doubling of the literature every ~3 years, consistent with a maturing field, expanding tooling and data availability, and post-2020 platform adoption. Model diagnostics and sensitivity checks support the robustness of this conclusion. Overdispersion was mild (Pearson $\chi^2/df = 1.21$), justifying retention of standard errors for the Poisson specification, a negative-binomial GLM delivered a closely aligned effect size (RR = 1.241, 95% CI 1.060–1.453, $p = 0.0073$), indicating that the inference is not an artifact of distributional assumptions. The convergence between a distribution-free trend test (Mann–Kendall with Sen's slope) and two count-regression formulations (Poisson and negative binomial) strengthens confidence in the presence and direction of the trend. Two interpretive nuances merit emphasis. First, the difference between the absolute slope (≈0.55 papers/year) and the multiplicative rate (≈26.5% per year) reflects low early-period counts: relative growth can be large even when absolute increments remain modest. Second, the Mann–Kendall test establishes monotonicity but does not model curvature; visual inspection and, if warranted, segmented or spline-based regressions could explore whether inflection points (e.g., around 2015 or 2020) contributed disproportionately to the aggregate increase. While the upward trajectory is unambiguous, it should be contextualized by limitations of the corpus construction (database coverage, English-language focus, keyword design) and potential secular confounders (indexing changes, evolving terminology). Future work could preregister search protocols, report inter-rater reliability for screening/coding, and add formal change-point analyses to pinpoint periods of accelerated growth. Even with these caveats, the observed compounding suggests sufficient critical mass to justify standardized reporting, comparative benchmarks, and meta-analytic syntheses in this research area.

The review's model chronology (Table 1) highlights a layered evolution: traditional pedagogical models structured goals and content; student/expert models introduced explicit user and domain representations; and, more recently, NLP/Transformers, knowledge graphs, and adaptive engines operationalized personalization at scale. Methodologically, the prominence of adaptive learning systems and knowledge-graph construction (Figure 9) reflects a field-wide shift from heuristic sequencing toward data-driven, semantically grounded decision-making that supports real-time feedback loops and dynamic content selection. Limitations frequently relate to the narrow subject coverage, uneven methodological rigor, and challenges around fairness, privacy (e.g., emotion recognition and continuous monitoring), and deployment in resource-constrained settings. These findings are consistent with a broader methodological evolution from classical pedagogical frameworks (e.g., RBT, FSLSM) to deep learning, NLP/Transformer architectures, and immersive XR environments, especially after 2020.

6. Conclusion

This systematic review of 26 studies (2010–2024) drawn from an initial corpus of 233 publications shows a decisive shift in educational AI toward personalization and adaptivity, supported by knowledge graphs, learning analytics, and, more recently, Transformer-based NLP alongside immersive VR/3D tools. Research activity accelerated markedly after 2015 with pronounced surges in 2021–2022, reflecting both methodological maturation and the pandemic-driven expansion of digital platforms. Subject coverage remains concentrated in General Education and Programming, with comparatively limited penetration in mathematics, chemistry, pedagogy, English, and computer science, while the geographic distribution of publications is centered in Asia (notably India and China) with contributions from the United States and parts of Europe. At the modeling layer, classical Student and Expert Models persist as the backbone of personalization, with modern stacks layering semantic representations and real-time analytics to tailor trajectories, diagnose difficulties, and anticipate outcomes.

Taken together, these results indicate that AI-enabled education is moving from heuristic sequencing toward semantically grounded, data-driven orchestration that can individualize pacing and content while offering teacher-facing diagnostics. However, narrow subject coverage, uneven methodological rigor, and open questions around privacy, fairness, and generalizability, especially in underrepresented or resource-constrained contexts, limit strong causal claims and hinder equitable scaling. We conclude that future progress hinges on: (i) standardized reporting that enables meta-analysis, (ii) rigorous, multi-site evaluations beyond general education/programming, (iii) integration of explainable, teacher-centered workflows, and (iv) governance frameworks that address ethical sensing and bias. With these foundations, next-generation systems can translate technical advances into durable, equitable learning gains at scale.

References

[1] L. Csépányi-Fürjes and L. Kovács, "Evolving graph based knowledge space model for tutoring systems," *Pollack Periodica,* vol. 19, no. 3, pp. 40-45, 2024. https://doi.org/10.1556/606.2024.01058

[2] D. Deepika, G. Sindhu, K. Nikhil, K. B. Sree, and Y. H. Vardhan, "Generation of smart text book using AI," in *2023 4th IEEE Global Conference for Advancement in Technology (GCAT) (pp. 1-6). IEEE*, 2023.

[3] A. Barlybayev and A. Sharipbay, "An intelligent system for learning, controlling and assessment knowledge," *Information (Japan),* vol. 18, no. 5, pp. 1817-1827, 2015.

[4] R. Al-Otaibi and S. Gamalel-Din, "Intelligent querying for adaptive course preparation and delivery in e-learning," in *The Proceedings of the Ninth IASTED International Conference on Webbased Education, Sharm El-Sheikh*, 2010.

[5] S. Dutt and N. J. Ahuja, "An intelligent HCI based tutoring system for child-centric learning environment," *Multimedia Tools and Applications,* vol. 83, pp. 85575-85596, 2024. https://doi.org/10.1007/s11042-024-20052-x

[6] A. W. Fodouop Kouam, "The effectiveness of intelligent tutoring systems in supporting students with varying levels of programming experience," *Discover Education,* vol. 3, p. 278, 2024. https://doi.org/10.1007/s44217-024-00385-3

[7] K. Siripongdee, P. Pımdee, and S. Tuntıwongwanıch, "A blended learning model with IoT-based technology: Effectively used when the COVID-19 pandemic?," *Journal for the Education of Gifted Young Scientists,* vol. 8, no. 2, pp. 905-917, 2020. https://doi.org/10.17478/jegys.698869

[8] G. Suddul, C. Lillmond, and S. Armoogum, "A smart virtual tutor with facial emotion recognition for online learning," in *2022 IEEE Zooming Innovation in Consumer Technologies Conference (ZINC) (pp. 67-72). IEEE*, 2022.

[9] K. Meenakshi, R. Sunder, A. Kumar, and N. Sharma, "An intelligent smart tutor system based on emotion analysis and recommendation engine," in *2017 International Conference on iot and Application (iciot) (pp. 1-4). IEEE*, 2017.

[10] A. Iyamuremye *et al.*, "Utilization of artificial intelligence and machine learning in chemistry education: A critical review," *Discover Education,* vol. 3, p. 95, 2024. https://doi.org/10.1007/s44217-024-00197-5

[11] T. Li and X. Zou, "Informatization of constructive English learning platform based on artificial intelligence algorithm," in *2022 International Conference on Frontiers of Artificial Intelligence and Machine Learning (FAIML)*, 2022: IEEE.

[12] J. C. Janet, "Intelligent Web-based English e-learning tutor with Data Mining technique," *Indian Journal of Public Health Research & Development,* vol. 9, no. 3, pp. 436-439, 2018.

[13] L. Fu *et al.*, "Sinkt: A structure-aware inductive knowledge tracing model with large language model," in *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, 2024.

[14] D. Arunoda, S. Walpola, S. Piumira, A. Athukorala, T. Thilakarathna, and S. Chandrasiri, "Deep learning-based e-learning solution for identifying and bridging the knowledge gap in primary education," in *2023 International Research Conference on Smart Computing and Systems Engineering (SCSE) (Vol. 6, pp. 1-8). IEEE*, 2023.

[15] A. C. Yang, J.-Y. Lin, C.-Y. Lin, and H. Ogata, "Enhancing python learning with PyTutor: Efficacy of a ChatGPT-Based intelligent tutoring system in programming education," *Computers and Education: Artificial Intelligence,* vol. 7, p. 100309, 2024. https://doi.org/10.1016/j.caeai.2024.100309

[16] T. Tojo, N. M. Noh, O. Ono, and R. Yusof, "Intelligent decision supporting tutor in virtual group operation control and management based on e-learning system," in *2015 10th Asian Control Conference (ASCC) (pp. 1-6). IEEE*, 2015.

[17] P. Sharma and M. Harkishan, "Designing an intelligent tutoring system for computer programing in the Pacific," *Education and Information Technologies,* vol. 27, pp. 6197-6209, 2022. https://doi.org/10.1007/s10639-021-10882-9

[18] H. G. Sigarchian *et al.*, "Hybrid e-TextBooks as comprehensive interactive learning environments," *Interactive Learning Environments,* vol. 26, no. 4, pp. 486-505, 2018. https://doi.org/10.1080/10494820.2017.1343191

[19] M. Li, "System construction of immersive smart teaching environment based on virtual spatial data multi-dimensional imaging technology," in *2022 International Conference on Edge Computing and Applications (ICECAA) (pp. 938-941). IEEE*, 2022.

[20] J. Schreurs, "Smart teaching technologies used in a hybrid learning course model," in *Proceedings of ICERI2013 Conference, 18th-20th November*, 2013.

[21] J. R. Carbonell, "AI in CAI: An artificial-intelligence approach to computer-assisted instruction," *IEEE Transactions on Man-Machine Systems,* vol. 11, no. 4, pp. 190–202, 1970.

[22] B. Joyce and M. Weil, *Models of teaching*. Englewood Cliffs, NJ: Prentice-Hall, 1972.

[23] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Engineering Education,* vol. 78, no. 7, pp. 674–681, 1988.

[24] L. W. Anderson and D. R. Krathwohl, *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*, Complete ed. New York: Longman, 2001.

[25] M. J. Page *et al.*, "PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews," *bmj*, vol. 372, 2021. https://doi.org/10.1136/bmj.n160

[26] K. Chrysafiadi and M. Virvou, "PerFuSIT: Personalized fuzzy logic strategies for intelligent tutoring of programming," *Electronics,* vol. 13, no. 23, p. 4827, 2024.

[27] S. Nithya and K. Apinayaprethi, "Significance of knowledge graph in SMART learning," in *2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA). IEEE*, 2023.
[28] G. o. I. Ministry of Education, *National education policy 2020*. New Delhi, India: Government of India, 2020.
[29] P. Sihag and Vibha, "Transforming and reforming the Indian education system with artificial intelligence," *Digital Education Review*, vol. 45, pp. 98–105, 2024.
[30] State Council of the People's Republic of China, *New generation artificial intelligence development plan*. Beijing, China: State Council, 2017.