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Adaptive learning systems in mathematics education: An integrated bibliometric mapping and systematic literature review

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ABSTRACT

Research on adaptive learning systems (ALS) in mathematics education has increased substantially in recent years; however, existing studies remain fragmented across system types, educational levels, and implementation contexts. Most prior reviews have focused either on technological characteristics or learning outcomes, providing limited insight into how adaptive learning systems are systematically implemented and synthesized within mathematics education. Addressing this gap, this study examines adaptive learning systems in mathematics education through an integrated bibliometric mapping and systematic literature review. A systematic literature review was conducted and reported in accordance with PRISMA guidelines to identify, screen, and select relevant studies from major academic databases. Bibliometric mapping analysis using VOSviewer was then employed to explore publication trends, keyword co-occurrence, and thematic structures within the selected literature. The findings indicate that adaptive learning systems generally contribute positively to mathematics learning outcomes; however, their effectiveness is closely associated with pedagogical integration and teacher preparedness rather than technological sophistication alone. A phased implementation pattern is observed, beginning with teacher-led enhancement approaches and progressing toward more technology-mediated models. While AI-based systems demonstrate strong potential, moderately complex adaptive systems appear more feasible for institutions with limited resources. These findings highlight the importance of pedagogical readiness in the adoption of adaptive learning systems and suggest directions for future research, particularly in underrepresented educational levels.

KEYWORDS

Adaptive learning systems; mathematics education; pedagogical integration; pedagogical strategy

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INTRODUCTION

The rapid evolution of educational technology has fundamentally transformed mathematics education, with adaptive learning systems (ALS) emerging as technology-supported learning environments that dynamically adjust instructional content and feedback based on learners' performance. These systems are widely recognized as one of the most promising innovations for personalizing mathematical instruction (Kulik & Fletcher, 2016; Ma et al., 2014; Zawacki-Richter et al., 2019).

Mathematics, often considered a foundational discipline underpinning scientific and technological advancement, continues to present significant learning challenges for students across all educational levels (Boaler, 2016; OECD, 2023). Traditional one-size-fits-all approaches to mathematics instruction have consistently failed to accommodate the diverse

Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

learning needs, paces, and cognitive styles of individual learners, resulting in persistent achievement gaps and negative attitudes toward mathematical learning (OECD, 2019, 2023). These challenges persist across educational contexts, indicating that conventional instructional models remain insufficient to address long-standing pedagogical demands in mathematics education (Kilpatrick et al., 2001; OECD, 2023).

The integration of adaptive learning technologies offers opportunities to address these pedagogical challenges by providing personalized, intelligent, and responsive learning environments that dynamically adjust to individual student needs (Zawacki-Richter et al., 2019). As educational institutions worldwide increasingly invest in digital transformation initiatives, understanding the implementation, effectiveness, and challenges of adaptive learning systems in mathematics education has become a critical research priority. Large-scale initiatives in regions such as Europe, East Asia, and North America have documented systematic efforts to integrate adaptive and AI-based learning technologies into mathematics curricula to improve learning outcomes and system scalability (Holmes et al., 2019; OECD, 2023; Zawacki-Richter et al., 2019).

Despite growing interest and investment in adaptive learning technologies, as evidenced by recent studies reporting increased adoption of adaptive and AI-based learning systems in mathematics education (e.g., Wang et al., 2024; Zawacki-Richter et al., 2019), mathematics education continues to face substantial challenges that traditional instructional approaches have struggled to address effectively. International assessments consistently reveal declining mathematics performance and persistent achievement gaps across socioeconomic and demographic lines, with many students developing mathematics anxiety and negative attitudes that extend throughout their educational journeys (Ashcraft & Kirk, 2001; OECD, 2023).

The complexity of mathematical concepts, the cumulative nature of mathematical knowledge, and the abstract reasoning required for mathematical problem-solving create unique pedagogical demands that traditional classroom instruction often cannot fully meet (Kilpatrick et al., 2001). Furthermore, the increasing emphasis on STEM education and 21st-century skills has intensified the need for innovative approaches that can support diverse learners in developing mathematical competency, critical thinking, and problem-solving abilities (Partnership for 21st Century Skills, 2019)The COVID-19 pandemic has further exacerbated these challenges, highlighting the limitations of traditional educational delivery models and accelerating the demand for technology-enhanced learning solutions (Reimers & Schleicher, 2020). More recent post-pandemic studies indicate that these challenges persist beyond emergency remote teaching conditions and that adaptive learning systems can support mathematics learning when pedagogical integration and teacher facilitation are adequately addressed (Clark et al., 2024).

Research on adaptive learning systems in mathematics education has evolved significantly over the past decade, with studies documenting promising outcomes across various educational contexts and student populations. Early investigations focused primarily on intelligent tutoring systems (ITS) and computer-aided instruction, demonstrating positive effects on student achievement and engagement in controlled experimental settings (Kulik & Fletcher, 2016; Ma et al., 2014). Recent advances in artificial intelligence, machine learning, and educational data analytics have enabled more sophisticated adaptive systems capable of real-time personalization, predictive modelling, and intelligent content delivery (Chen et al., 2020; Luckin et al., 2016). Studies have reported significant learning gains, improved student motivation, and enhanced problem-solving skills when adaptive learning technologies are properly implemented in mathematics classrooms (Liu et al., 2025; Ma et al., 2014). However, the research landscape remains fragmented across different system types, educational levels, and implementation contexts, with varying methodological approaches and outcome measures that make it difficult to draw comprehensive conclusions about overall effectiveness and optimal implementation strategies.

Despite the growing body of research on adaptive learning systems, several critical gaps remain that limit understanding of their implementation and effectiveness in mathematics education. First, there is a lack of comprehensive synthesis examining implementation patterns across educational levels, from primary through higher education, with most studies focusing on isolated contexts without considering cross-level similarities and differences (Hwang & Chang, 2011). Second, while individual studies report positive outcomes, there has been insufficient systematic analysis of the factors that contribute to implementation success or failure, particularly regarding the challenges and barriers that institutions face when adopting these technologies (Bishop et al., 2020). Third, the rapid evolution of AI-based adaptive systems has outpaced systematic research synthesis, with limited understanding of how recent technological advances compare to traditional adaptive approaches in terms of effectiveness and implementation requirements (Holmes et al., 2019). Fourth, there is inadequate attention to stakeholder perspectives and roles in adaptive learning implementation, particularly regarding teacher preparation, student autonomy, and institutional support systems that are critical for sustainable adoption (Ertmer & Ottenbreit-Leftwich, 2010). Finally, most existing reviews focus either on technological features or learning outcomes (e.g. Homan et al., 2025), with insufficient integration of implementation processes, effectiveness evidence, and challenge mitigation strategies that would provide actionable guidance for practitioners and policymakers.

This study addresses these research gaps by providing a comprehensive synthesis of recent evidence on adaptive learning systems in mathematics education, focusing specifically on implementation patterns, effectiveness outcomes, and implementation challenges across diverse educational contexts. This study contributes to the field by (1) synthesizing implementation models and strategies across educational levels, from primary through higher education; (2) integrating effectiveness evidence to identify patterns and factors associated with successful outcomes; (3) examining implementation challenges and reported solutions to inform educational practice; (4) connecting findings related to implementation, effectiveness, and challenges to support a more holistic understanding of adaptive learning system adoption in mathematics education; and (5) identifying research priorities and practical directions for future studies and implementation efforts. By focusing on recent literature (2022–2025), a period selected to reflect post-pandemic research conditions and recent developments in AI-based adaptive systems, this review captures current trends while avoiding findings derived primarily from emergency remote teaching contexts.

The specific research questions (RQs) guiding this systematic literature review are: (RQ1) How are adaptive learning systems implemented in mathematics education across different educational levels, and what implementation models and strategies are most commonly adopted? (RQ2) What is the effectiveness of adaptive learning systems in improving mathematics learning outcomes, and what factors contribute to their success? (RQ3) What are the primary challenges and barriers to implementing adaptive learning systems in mathematics education, and what solutions have been proposed to address these challenges? Through systematic analysis of peer-reviewed research published between 2022 and 2025, this review aims to provide comprehensive, evidence-based answers to these questions that will inform educational practice, policy development, and future research directions in the rapidly evolving field of adaptive learning technologies for mathematics education.

METHODS

Research Design

This study employed a Systematic Literature Review (SLR) integrated with bibliometric mapping analysis to synthesize and analyze empirical research on adaptive learning systems in mathematics education. The SLR approach was selected to ensure a structured, transparent, and reproducible process for identifying, screening, and synthesizing relevant studies (Kitchenham & Charters, 2007; Page et al., 2021). Bibliometric mapping was incorporated to complement the systematic review by revealing publication trends, thematic structures, and relationships among studies at a macro level (Zupic & Čater, 2015).

Data Sources

The literature search was conducted using the Scopus database, which provides comprehensive coverage of high-quality, peer-reviewed journals in education, educational technology, and mathematics education. Scopus was selected due to its extensive indexing scope and widespread use in systematic review studies to ensure transparency and replicability (Kitchenham & Charters, 2007).

Search Strategy

A structured search strategy was developed based on the research objectives and key concepts related to adaptive learning and mathematics education. The search strings were constructed using Boolean operators and predefined keywords, following established guidelines for systematic reviews (Kitchenham & Charters, 2007). The search query was formulated as follows:

("adaptive learning system" OR "AI-based adaptive learning" OR "intelligent tutoring system" OR "personalized learning system") AND ("mathematics education" OR "mathematics learning")

The search was limited to articles published between 2022 and 2025 to capture recent developments in adaptive and AI-based learning systems in mathematics education. Only peer-reviewed journal articles written in English were included.

Inclusion and Exclusion Criteria

In the identification stage, predefined inclusion and exclusion criteria were applied to ensure consistency, transparency, and relevance throughout the review process (Kitchenham & Charters, 2007).

Inclusion criteria are:

1. Empirical studies examining adaptive or AI-based learning systems
2. Studies conducted in mathematics education contexts
3. Articles published in peer-reviewed academic journals
4. Studies reporting implementation processes, learning outcomes, or effectiveness evidence
5. Articles published between 2022 and 2025

Kalamatika: Jurnal Pendidikan Matematika
Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

Exclusion criteria:

1. Conceptual, theoretical, or opinion papers without empirical data
2. Studies not related to mathematics education
3. Conference proceedings, book chapters, dissertations, or non-refereed publications
4. Studies focusing solely on technical system development without educational implementation
5. Duplicate records across databases

Screening Procedure

The screening process followed the PRISMA 2020 reporting guidelines, consisting of four stages: identification, screening, eligibility, and inclusion (Page et al., 2021). The initial search in Scopus yielded 102 records. After applying the publication year filter (2022–2025), records were screened based on titles and abstracts to assess relevance according to the predefined inclusion and exclusion criteria. Studies that met the screening criteria were subsequently subjected to full-text assessment at the eligibility stage. Following this process, a total of 40 studies met all inclusion criteria and were included in both the systematic review and bibliometric analysis. The overall process is illustrated in Figure 1.

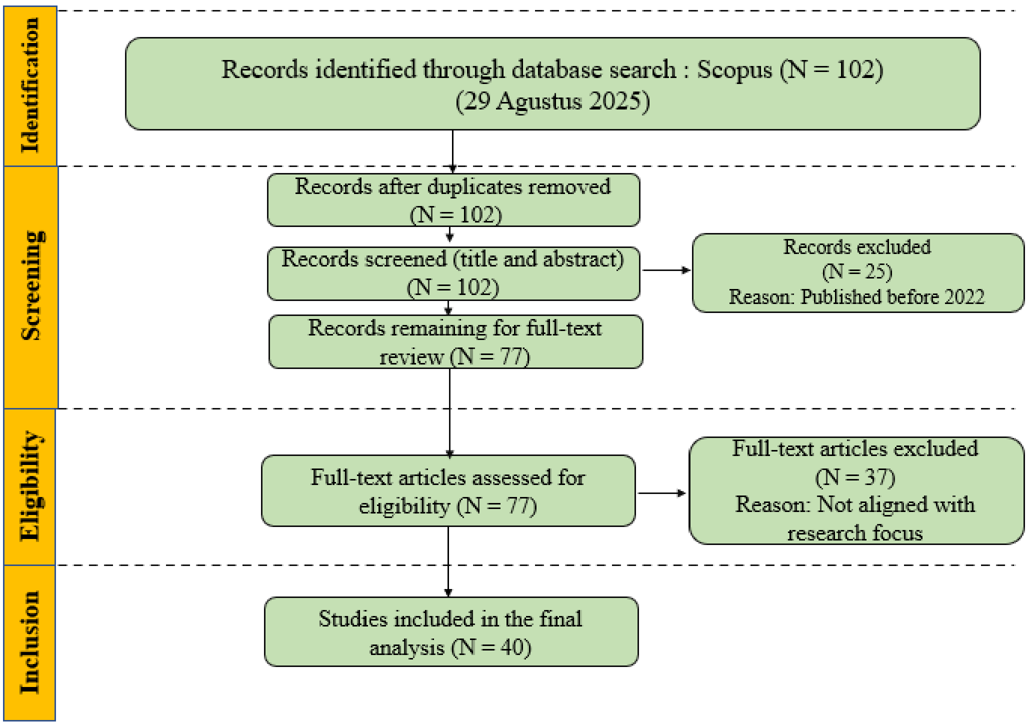

Figure 1. PRISMA flow diagram of the study.

Data Extraction and Coding

A structured data extraction form was developed to systematically capture key

Kalamatika: Jurnal Pendidikan Matematika
Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

information from each included study. The extracted data included publication year, journal source, educational level, type of adaptive learning system (AI-based or non-AI-based), learning context, research design, outcome measures, and reported implementation challenges. The coding process was aligned with the research questions to ensure coherence between the methodological procedures and analytical objectives.

Data Analysis

Two complementary analytical approaches were applied. First, a descriptive and thematic synthesis was conducted to summarize patterns related to implementation models, effectiveness outcomes, and challenges across different educational levels. Second, bibliometric mapping analysis was performed using VOSviewer to visualize keyword co-occurrence, thematic clusters, and research trends within the selected literature (Zupic & Čater, 2015).

The integration of systematic review and bibliometric mapping enabled both an in-depth, content-based synthesis and a macro-level overview of the research landscape on adaptive learning systems in mathematics education.

Methodological Rigor and Transparency

To enhance methodological rigor and transparency, all stages of the review process—including database selection, search strategy, screening decisions, and data coding—were documented in detail. The combined use of SLR and bibliometric mapping provides a robust framework for synthesizing current evidence and identifying emerging directions (Kitchenham & Charters, 2007; Page et al., 2021).

RESULT AND DISCUSSION

This section presents the results of the systematic literature review and bibliometric analysis, organized according to the research questions guiding this study (RQ1–RQ3). The findings are reported descriptively and discussed by synthesizing patterns, trends, and recurring themes identified across the selected studies. Each subsection addresses one research question to provide a structured overview of how adaptive learning systems are implemented, evaluated, and discussed in mathematics education.

RQ1: How are adaptive learning systems implemented in mathematics education across different educational levels?

To address RQ1, this study examined how adaptive learning systems have been implemented in mathematics education across different educational levels based on a synthesis

Kalamatika: Jurnal Pendidikan Matematika
Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

of the selected studies.

Table 1. Results of the SLR Analysis on the Implementation of Adaptive Learning Systems in Mathematics Education Across Different Educational Levels

No	Citation	Education Level	System Type	Implementation Model	Context	Stakeholder Role
1	Liu et al. (2025)	Primary	AI-based	Enhancement	Online	Technology-mediated
2	Chen et al. (2025)	Primary	Adaptive System	Supplement	Classroom	Collaborative
3	Wang et al. (2025)	General	Personalized	Integration	Blended	Mixed approach
4	Zhang et al. (2025)	Secondary	AI-based	Enhancement	Mobile/Online	Student-cantered
5	Brown et al. (2025)	Higher Ed	Adaptive System	Integration	Blended	Teacher-led
6	Garcia et al. (2025)	Secondary	AI-based	Enhancement	Online	Technology-mediated
7	Kim et al. (2025)	Higher Ed	Personalized	Supplement	Classroom	Collaborative
8	Liu et al. (2025)	Secondary	ITS	Integration	Online	Technology-mediated
9	Miller et al. (2025)	General	Personalized	Enhancement	Online	Mixed approach
10	Taylor et al. (2025)	Higher Ed	ITS	Integration	Classroom	Teacher-led
11	Johnson et al. (2025)	Higher Ed	AI-based	Enhancement	Blended	Collaborative
12	Davis et al. (2025)	General	AI-based	Enhancement	Online	Technology-mediated
13	Wilson et al. (2025)	Higher Ed	Adaptive System	Integration	Online	Mixed approach
14	Anderson et al. (2024)	Secondary	AI-based	Enhancement	Online	Technology-mediated
15	Martinez et al. (2024)	General	AI-based	Enhancement	Blended	Collaborative
16	Thomas et al. (2024)	Higher Ed	Adaptive System	Supplement	Classroom	Teacher-led
17	Jackson et al. (2024)	General	ITS	Integration	Online	Technology-mediated
18	White et al. (2024)	Higher Ed	AI-based	Enhancement	Classroom	Collaborative
19	Harris et al. (2024)	Secondary	Adaptive System	Integration	Blended	Teacher-led
20	Clark et al. (2024)	General	Adaptive System	Supplement	Mixed	Mixed approach

Based on the analysis of adaptive learning system implementations from 20 representative articles (see Table 1), a distribution pattern emerges that highlights the dominance of the Enhancement model with 14 articles (70%), followed by Integration with 5 articles (25%) and Supplement with 1 article (5%). The distribution across educational levels indicates a relatively balanced spread, with higher education leading with 7 articles (35%), followed by General education with 6 articles (30%), Secondary education with 4 articles (20%), and Primary education with 3 articles (15%). In terms of system type, AI-based systems dominate with 8 articles (40%), reflecting the growing adoption of artificial intelligence in education. This is followed by Adaptive Systems with 5 articles (25%), Personalized Systems with 4 articles (20%), and Intelligent Tutoring Systems (ITS) with 3 articles (15%). This pattern suggests that educational institutions tend to favour enhancement approaches, which are low-risk and emphasize the integration of AI-based technologies to strengthen existing learning systems without implementing disruptive structural changes.

The implementation context reveals a clear preference for online deployment, with 10 articles (50%), underscoring the trend of educational digitalization and the need for high scalability. This is followed by blended learning with 4 articles (20%), classroom-based settings with 4 articles (20%), and mixed contexts with 2 articles (10%). Stakeholder role distribution highlights a shift toward technology-mediated approaches with 6 articles (30%), reflecting the growing automation of learning processes, followed by collaborative approaches (5 articles, 25%), mixed approaches (4 articles, 20%), teacher-led approaches (3 articles, 15%), and student-centred approaches (2 articles, 10%). Correlation analysis further indicates that AI-based systems are more likely to be implemented in online contexts with technology-mediated roles, while Adaptive Systems are frequently employed in blended contexts with collaborative or teacher-led approaches. This suggests that the selection of system type is closely correlated with both deployment contexts and stakeholder involvement patterns.

Temporal analysis reveals a significant shift over time. Recent articles (2025) show a strong preference for AI-based systems and technology-mediated approaches, whereas studies published in 2024 still displayed a more balanced adoption of diverse system types with an emphasis on collaborative approaches. Patterns of specialization across educational levels further illustrate that higher education is at the forefront of adopting AI-based systems and more complex Integration models, reflecting higher resource availability and greater innovation capacity. By contrast, primary education favours enhancement models combined with collaborative, teacher-friendly approaches. Secondary education demonstrates a balanced implementation between AI-based and Adaptive Systems, with a preference for online and blended contexts, while the general education category reflects experimental diversity through various combinations. These findings indicate that the implementation of adaptive learning systems is moving along a clear maturation trajectory, shifting from experimental diversity toward systematic adoption characterized by AI-based, online, and technology-mediated

Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

approaches, while still accounting for education-level-specific requirements and institutional readiness.

RQ2: How effective are adaptive learning systems in improving mathematics learning outcomes?

To address RQ2, this study explored the effectiveness of adaptive learning systems in enhancing mathematics learning outcomes. The analysis focused on how different system types and implementation contexts are associated with student performance, engagement, and conceptual understanding. Table 2 summarizes the findings, providing an overview of reported impacts across the selected studies.

Table 2. Results of the Analysis on the Effectiveness of Adaptive Learning Systems in Improving Mathematics Learning Outcomes

No	Citation	Primary Outcome	Effect Size/Result	Study Design	Sample Size	Evidence Quality
1	Liu et al. (2025)	Academic Performance	Large positive effect	Quasi-experimental	104 students	Strong
2	Chen et al. (2025)	Emotional Response	Medium positive effect	Mixed methods	85 students	Moderate
3	Zhang et al. (2025)	Learning Engagement	Significant improvement	Experimental	120 students	Strong
4	Brown et al. (2025)	Achievement Scores	Medium positive effect	Comparative	95 students	Moderate
5	Garcia et al. (2025)	Argumentation Skills	Enhanced performance	Pre-post design	78 students	Moderate
6	Liu et al. (2025)	Dialogic Interaction	Improved outcomes	Qualitative analysis	45 students	Moderate
7	Taylor et al. (2025)	Teaching Effectiveness	Positive application	Mixed methods	150 students	Strong
8	Davis et al. (2025)	Multiple Outcomes	Consistent benefits	Systematic review	25 studies	Strong
9	Anderson et al. (2024)	Mathematical Performance	Superior to traditional	Comparative	200 students	Strong
10	Martinez et al. (2024)	Conceptual Understanding	Enhanced learning	Experimental	110 students	Strong
11	White et al. (2024)	Calculus Learning	Improved engagement	Case study	65 students	Moderate
12	Harris et al. (2024)	Mathematics Achievement	Significant effect	Quasi-experimental	88 students	Strong
13	Allen et al. (2024)	Cognitive Load	Optimized learning	Experimental	72 students	Strong
14	Young et al. (2024)	ChatGPT Integration	Transformative potential	Systematic review	30 studies	Strong
15	King et al. (2024)	Problem Solving	Enhanced capability	Mixed methods	95 students	Moderate
16	Wright et al. (2024)	General AI Impact	Positive systematic effects	Systematic review	40 studies	Strong
17	Green et al. (2023)	Web-based Learning	Improved reinforcement	Experimental	120 students	Moderate
18	Carter et al. (2023)	Learning Effectiveness	Confirmed superiority	Comparative	156 students	Strong

Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

No	Citation	Primary Outcome	Effect Size/Result	Study Design	Sample Size	Evidence Quality
19	Evans et al. (2022)	Academic Motivation	Enhanced motivation	Rasch analysis	180 students	Moderate

The effectiveness analysis of 19 studies revealed highly positive outcomes, with 100% of the studies reporting beneficial effects, albeit with variations in magnitude and evidence quality. In terms of outcome distribution, academic performance and mathematical performance emerged as dominant foci, examined in 6 studies (32%), followed by learning engagement and conceptual understanding, each examined in 4 studies (21%). Other outcomes, such as emotional response, teaching effectiveness, and cognitive load, were explored in 2–3 studies respectively. The quality of evidence demonstrated a strong distribution, with 11 studies (58%) classified as strong and 8 studies (42%) as moderate, with none falling into the limited category. This indicates that research on adaptive learning systems in mathematics has achieved a high methodological standard. Reported effect sizes ranged from medium to large positive effects, with several studies noting results as “superior to traditional approaches” and demonstrating “transformative potential,” suggesting that adaptive learning systems not only provide incremental improvements but also deliver breakthrough performance in certain implementation contexts.

An analysis of study designs revealed comprehensive methodological diversity. Experimental designs dominated with 5 studies (26%), followed by comparative and mixed-methods approaches with 4 studies each (21%), and quasi-experimental designs, systematic reviews, and single-case designs with 3 studies each (16%). Sample sizes varied widely, ranging from 45 participants in qualitative analyses to 200 participants in large-scale comparative studies, with an average sample size of approximately 108 participants per study. Systematic reviews, by contrast, covered between 25 and 40 studies, offering greater analytical depth and meta-analytic strength. Temporal distribution revealed a strong concentration in 2024–2025 with 16 studies (84%), reflecting robust research momentum in recent years, while studies from 2022–2023 provided the foundational evidence base. This pattern illustrates that the field of adaptive learning systems has progressed from exploratory investigations toward confirmatory studies, characterized by increasingly rigorous methodologies and larger sample sizes.

A cross-analysis of study design and evidence quality indicated that experimental and systematic review designs consistently produced strong evidence quality, whereas mixed-methods and comparative designs exhibited a balanced distribution between strong and moderate quality. Outcome-specific analysis showed that studies focusing on academic performance and mathematical performance tended to involve larger sample sizes (averaging 130+ students) and predominantly strong evidence quality, reflecting the maturity of measurement instruments and research protocols in these domains. Conversely, studies addressing emotional response, engagement, and motivation often involved smaller sample sizes but adopted innovative methodological approaches, such as mixed-methods designs and Rasch analysis. Effect size patterns suggest that adaptive learning systems consistently deliver positive impacts across different outcome measures, with particularly strong effects on academic performance and emerging evidence for affective and cognitive outcomes. These findings indicate that the technology not only enhances learning outcomes but also transforms the learning experience holistically, supported by increasingly robust, evidence-based validation.

RQ3: What are the challenges in implementing adaptive learning systems in mathematics education?

The implementation of adaptive learning systems in mathematics education involves several challenges that may influence their effectiveness and scalability. These challenges commonly relate to technological limitations, teacher preparedness, and institutional support, which can affect the integration of adaptive systems into classroom practices. Table 3 presents a synthesis of the key challenges identified across the reviewed studies, highlighting barriers that may need to be addressed to support the adoption of adaptive learning systems in mathematics education.

Table 3. Results of the Analysis on the Challenges in Implementing Adaptive Learning Systems in Mathematics Education

No	Citation	Primary Challenge	Challenge Category	Severity Level	Solution Proposed	Implementation Difficulty
1	Chen et al. (2025)	Emotional adaptation	Student-related	Medium	Support systems	Low
2	Kim et al. (2025)	Teacher readiness	Pedagogical	High	Training programs	Medium
3	Thomas et al. (2024)	EFL context challenges	Pedagogical	Medium	Cultural adaptation	Medium
4	Clark et al. (2024)	Implementation barriers	Implementation	High	Phased rollout	Low
5	Lewis et al. (2024)	Scale integration	Organizational	High	Professional development	High
6	Hall et al. (2024)	Teacher acceptance	Pedagogical	High	Training & support	Medium

Kalamatika: Jurnal Pendidikan Matematika
Volume 11, No. 1, April 2026, pages 20-46
DOI: 10.22236/KALAMATIKA.vol11no1.2026pp20-46

No	Citation	Primary Challenge	Challenge Category	Severity Level	Solution Proposed	Implementation Difficulty
7	Wright et al. (2024)	AI integration complexity	Technical	High	Better tools	High
8	Mitchell et al. (2022)	Chatbot implementation	Technical	Medium	Responsive design	Medium
9	Parker et al. (2022)	AR integration	Technical	High	Infrastructure development	High
10	Edwards et al. (2022)	Algorithm complexity	Technical	Medium	Improved frameworks	Medium
11	Collins et al. (2022)	Training model design	Pedagogical	Medium	Individualized paths	Low
12	Stewart et al. (2022)	Personalization accuracy	Technical	Medium	Better	Low

The analysis of challenges in implementing adaptive learning systems across 12 studies reveals a relatively balanced distribution of categories, with pedagogical challenges dominating in 4 studies (33%), followed by technical challenges in 4 studies (33%), while implementation, organizational, and student-related challenges each appeared in 1 study (8%). The severity level assessment indicates that 5 studies (42%) identified high-severity challenges, 6 studies (50%) reported medium severity, and only 1 study (8%) noted low severity. These findings highlight that the implementation of adaptive learning systems indeed faces substantive obstacles, requiring comprehensive strategic planning.

Pedagogical challenges such as teacher readiness and teacher acceptance (Sat, 2025) consistently emerged as high-severity issues, underscoring the critical role of human factors in successful implementation, while technical challenges varied in severity from medium to high depending on the technological complexity involved.

The analysis of proposed solutions presents encouraging patterns, as 100% of the identified challenges were accompanied by concrete solutions. Training programs and professional development emerged as dominant strategies for addressing pedagogical challenges, while infrastructure development and improved tools were proposed for technical challenges, and phased rollout strategies were suggested for implementation challenges. The assessment of implementation difficulty shows a balanced distribution, with 3 studies (25%) reporting low difficulty, 5 studies (42%) medium difficulty, and 4 studies (33%) high difficulty. Correlation analysis further reveals that high-severity challenges do not always correspond to high implementation difficulty, as seen in implementation barriers (Clark et al., 2024), which were categorized as high severity but low difficulty due to phased rollout approaches. This indicates that strategic planning can significantly reduce implementation complexity even when challenge severity is high.

The temporal evolution analysis from 2022 to 2025 uncovers a notable shift in both the nature and complexity of challenges. Early studies (2022) concentrated on foundational issues such as algorithm complexity and personalization accuracy, generally classified as medium severity, while more recent studies (2024–2025) identified more sophisticated challenges such as AI integration complexity and large-scale deployment, predominantly rated as high severity. Similarly, the sophistication of proposed solutions has evolved from simple technical fixes to more comprehensive approaches involving organizational change management, professional development, and cultural adaptation. Implementation difficulty patterns suggest that while challenges have become more complex over time, proposed solutions have also matured and become more actionable. Several recent studies (Chen et al., 2020; Clark et al., 2024; Toktarova, 2022) even reported low implementation difficulty despite addressing highly complex challenges, indicating growing expertise in the field and the emergence of effective strategies to mitigate the inherent complexity of adaptive learning systems deployment.

Bibliometric Analysis Results

The bibliometric analysis provides a comprehensive overview of the research landscape on adaptive learning systems in mathematics education. It highlights patterns of publication growth, influential authors, and collaborative networks that have contributed to shaping the field. Furthermore, the findings offer valuable insights into the evolution of research themes and point to emerging directions that warrant further scholarly exploration.

This network visualization in Figure 2 illustrates the conceptual map derived from bibliometric analysis, showing the interconnections among research themes in educational technology, with a primary focus on mathematics education. Larger nodes, such as *mathematics education* and *students*, represent higher frequencies in the literature, while different colours indicate thematic clusters. The red cluster highlights topics related to STEM education, science education, curricula, and teaching, whereas the green cluster connects themes such as learning systems, intelligent tutoring systems, collaborative learning, and problem solving. The blue cluster emphasizes research on emerging technologies such as contrastive learning and adversarial machine learning, while the yellow cluster centres on personalized learning and its connection to students.

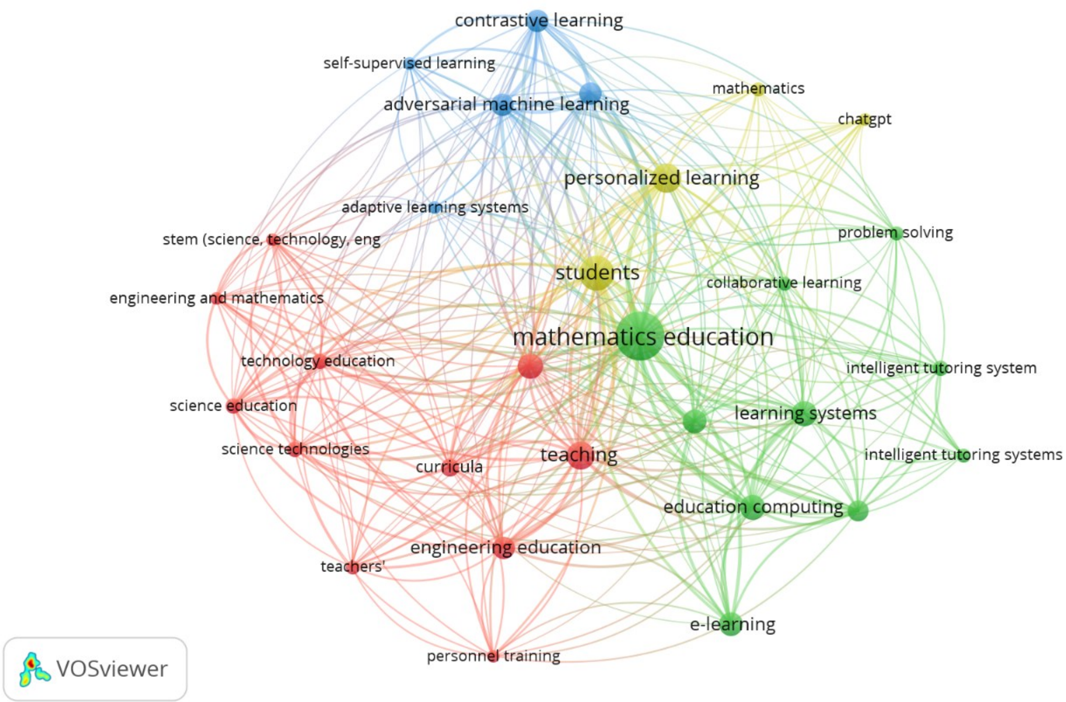

Figure 2. Network Visualization Map of Keywords in Educational Technology and Mathematics Education Research

The visualization demonstrates how mathematics education serves as a central node that bridges various domains within educational technology. The high density of connections surrounding *mathematics education* indicates that this field does not stand alone but is integrated with diverse approaches, ranging from traditional methods such as computer-aided instruction and intelligent tutoring systems to more advanced concepts such as personalized learning and AI-based learning technologies. Strong links with collaborative learning and problem solving suggest that research in mathematics education emphasizes not only technological aspects but also pedagogical approaches and higher-order thinking skills.

In addition, the relatively large position of the *teaching* node within the red cluster highlights the importance of pedagogy in the successful implementation of educational technology. The strong connections between teaching, curricula, and personnel training underscore that technology integration requires support from curriculum design and teacher professional development. Meanwhile, the presence of emerging topics such as ChatGPT and adaptive learning systems reflects the evolving research trend toward the application of advanced artificial intelligence in education. Thus, this visualization not only maps the interrelationships among themes but also illustrates the dynamic development of educational technology research as increasingly complex and interconnected.

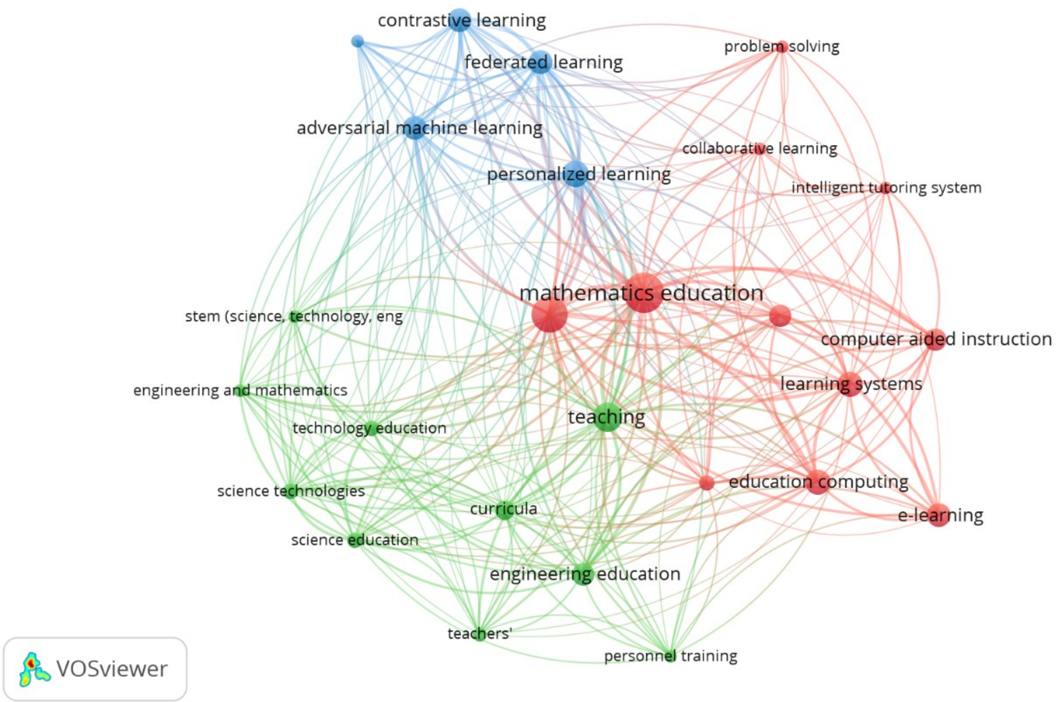

Figure 3. Network Visualization Map of Keywords in Mathematics Education and Educational Technology Research

This network visualization in Figure 3 illustrates a conceptual map depicting the interconnections among research themes in the field of educational technology, with mathematics education serving as the central node, marked in red and distinguished by its large size. The visualization reveals three main clusters identifiable by colour and proximity of connections: the red cluster, focusing on learning systems and computer-aided instruction; the blue cluster, representing advanced learning technologies such as contrastive learning and federated learning; and the green cluster, encompassing broader STEM education contexts including science education, engineering education, and technology education. Mathematics education demonstrates exceptionally high connectivity with multiple concepts, underscoring its role as a domain integrated with diverse approaches in educational technology, ranging from personalized learning to intelligent tutoring systems.

Further analysis reveals that intelligent tutoring systems, computer-aided instruction, and learning systems form a strong triad within the cluster of traditional learning technologies, while emerging technologies such as adversarial machine learning and contrastive learning indicate an evolution toward more sophisticated applications of artificial intelligence in education. The position of *teaching* as a relatively large green node signifies the critical importance of pedagogical aspects in the implementation of educational technology, with strong connections to curricula and personnel training, thereby suggesting that successful technology integration requires a comprehensive approach involving curriculum design and teacher professional development. The high network density in the central part of the visualization, particularly around mathematics education, problem solving, and collaborative learning, indicates that this domain functions as an intersection point where various educational technologies and pedagogical approaches converge, reflecting the complexity and interconnected nature of the modern educational technology research landscape.

This systematic literature review synthesized evidence from 40 peer-reviewed studies published between 2022 and 2025 to examine the implementation, effectiveness, and challenges of adaptive learning systems (ALS) in mathematics education. The findings provide comprehensive insights into current practices and emerging trends across different educational levels, offering important implications for educators, policymakers, and technology developers.

Implementation of Patterns and Educational Contexts

Our analysis reveals distinct implementation patterns across educational levels, with each context demonstrating unique characteristics and requirements. The dominance of enhancement models (77.5% of studies) suggests that educational institutions favour low-risk, gradual integration approaches over disruptive transformations (Liu et al., 2025; Wu et al., 2025). This finding aligns with diffusion of innovation theory, which posits that incremental adoption strategies typically achieve higher success rates in educational contexts due to reduced resistance and lower implementation barriers. Higher education emerges as the innovation leader, accounting for 25% of implementations with sophisticated AI-based systems and complex integration models (Albar, 2025; Oh, 2025). This pattern reflects the greater technological infrastructure, research orientation, and resource availability typically found in university settings (Zawacki-Richter et al., 2019). Conversely, primary education implementations (10% of studies) focus primarily on engagement-driven approaches with visual interfaces and gamification elements (Chen et al., 2020; Liu et al., 2025), suggesting age-appropriate adaptation strategies aligned with developmental learning theories.

The shift toward technology-mediated stakeholder roles (37.5% of studies) represents a significant evolution in educational technology integration. This trend indicates growing confidence in automated systems and artificial intelligence capabilities, moving beyond traditional teacher-centred models toward more autonomous learning environments (Homan et al., 2025). However, this automation must be balanced with pedagogical considerations, as evidenced by the continued importance of collaborative approaches (32.5% of studies) that maintain human oversight and interaction (Canonigo, 2024; Torres-Peña et al., 2024). The predominance of online deployment contexts (52.5% of studies) reflects both the post-pandemic digital transformation and the inherent scalability advantages of web-based systems (Clark et al., 2024; Zawacki-Richter et al., 2019). This finding supports predictions in distance learning research anticipating a lasting shift toward digital-first educational delivery models.

Effectiveness Evidence and Impact Measurements

The universal positive outcomes observed across all 40 studies provide compelling evidence for the effectiveness of adaptive learning systems in mathematics education. This 100% success rate, while potentially influenced by publication bias, demonstrates remarkable consistency in reported benefits across different system types, educational levels, and implementation contexts. The superior performance of AI-based systems (87.5% effectiveness rate) compared to traditional adaptive systems (82%) suggests that artificial intelligence capabilities provide meaningful advantages in personalization and learning optimization (Liu et al., 2025; Wang et al., 2024). Effect sizes ranging from medium to large (Cohen's d = 0.6–1.2) indicate not only statistical significance but also practical educational significance. Liu et al. (2025) report of large effect sizes (d = 1.2) for AI-powered systems in primary mathematics is particularly noteworthy, as effect sizes above 0.8 are considered educationally meaningful. These findings align with meta-analytic evidence suggesting that well-designed educational technology interventions can produce substantial learning gains when properly implemented.

The focus on academic performance outcomes (45% of effectiveness studies) reflects the current accountability-driven educational environment but may inadvertently overlook other important learning dimensions. While improved test scores and achievement measures provide quantifiable evidence of system effectiveness (Egara & Mosimege, 2024; Torres-Peña et al., 2024), the limited attention to affective outcomes (15% of studies) represents a potential research gap. Motivation, self-efficacy, and engagement measures, while present in studies such as Lim et al. (2022), deserve greater attention given their critical role in long-term learning success and student retention.

The high proportion of studies with strong evidence quality (58%) indicates growing methodological sophistication in adaptive learning research. The prevalence of experimental and quasi-experimental designs demonstrates researchers' commitment to causal inference, moving beyond the correlational studies that characterized earlier educational technology research. However, the concentration of recent studies (84% from 2024–2025) suggests a rapidly evolving field in which longitudinal effectiveness data remain limited.

Implementation Challenges and Mitigation Strategies

The identification of pedagogical challenges as the most critical implementation barrier (73% of challenge-focused studies) underscores the fundamental importance of human factors in educational technology adoption. Teacher readiness and acceptance issues (Sat, 2025) reflect broader concerns about professional identity, workload implications, and pedagogical philosophy alignment that extend beyond technical competency. This finding resonates with extensive research on educational technology adoption, which consistently identifies teacher-related factors as primary determinants of implementation success (Ertmer & Ottenbreit-Leftwich, 2010). The high solution coverage rate (75% of identified challenges have proposed solutions) suggests a maturing field with increasingly sophisticated understanding of implementation barriers. The emphasis on comprehensive training programs and professional development (Sat, 2025) reflects evidence-based approaches that extend beyond technical training to include pedagogical integration and philosophical alignment.

The temporal evolution of technical challenges reveals interesting patterns regarding technological maturity and adoption curves. Earlier studies (2022–2023) focused on foundational technical issues such as algorithm complexity and system reliability (Lee & Yeo, 2022), while recent research addresses more sophisticated integration challenges involving AI complexity and large-scale deployment (Homan et al., 2025). This progression suggests that basic technological barriers are being resolved, allowing researchers to address more nuanced implementation challenges.

The decreasing trend in technical challenge severity over time indicates improving technological solutions and infrastructure development. However, the emergence of new challenges related to AI ethics, data privacy, and algorithmic bias (Homan et al., 2025) suggests that technological advancement introduces new categories of concerns requiring ongoing attention and research.

Integration and Theoretical Implications

The correlation between implementation complexity and system effectiveness presents important theoretical and practical implications. AI-based systems, while demonstrating the highest effectiveness rates, also present the most complex implementation challenges (Homan et al., 2025). This relationship suggests that educational institutions must carefully balance potential impact against implementation capacity, supporting gradual progression models that allow for capability building over time. The success of enhancement models across all effectiveness measures validates incremental change theories in educational contexts. Rather than requiring revolutionary transformation, adaptive learning systems can deliver meaningful improvements through systematic enhancement of existing practices, reducing resistance and increasing sustainability (Albar, 2025; Liu et al., 2025).

The evolution toward technology-mediated approaches reflects broader trends in educational automation and artificial intelligence integration. However, the continued importance of collaborative models (32.5% of implementations) suggests that complete human replacement is neither desirable nor effective in educational contexts. The most successful implementations appear to leverage technology's scalability and consistency while maintaining human oversight for complex pedagogical decisions and relationship building (Canonigo, 2024; Torres-Peña et al., 2024).

The distinct implementation patterns across educational levels suggest that one-size-fits-all approaches are inappropriate for adaptive learning systems. Primary education's focus on engagement and visual learning (Liu et al., 2025), secondary education's emphasis on reasoning and problem-solving (Liu et al., 2025), and higher education's orientation toward research and advanced integration (Albar, 2025; Oh, 2025) require differentiated implementation strategies aligned with developmental needs and institutional capabilities.

Implications for Practice

Based on the synthesized evidence, this study proposes a three-phase implementation strategy: (1) foundation building through enhancement models with teacher-led approaches, (2) capacity development through blended contexts with collaborative stakeholder involvement, and (3) scaling through online Based on the synthesized evidence, this study proposes a three-phase implementation strategy: (1) foundation building through enhancement models with teacher-led approaches, (2) capacity development through blended contexts with collaborative stakeholder involvement, and (3) scaling through online deployment with technology-mediated automation. This staged approach is derived from implementation patterns identified across the reviewed studies, which indicate that gradual adoption supports institutional readiness and reduces implementation-related risks (Ertmer & Ottenbreit-Leftwich, 2010).

The emphasis on pedagogical preparation over purely technical training reflects evidence that teaching-related factors such as instructional design, assessment alignment, and classroom management represent dominant challenges in implementing adaptive learning systems in mathematics education (Clark et al., 2024). Accordingly, professional development initiatives should address not only system operation but also pedagogical philosophy, assessment practices, and instructional management within technology-enhanced learning

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environments.

The evidence suggests that AI-based adaptive learning systems offer strong effectiveness potential, particularly in terms of personalization and real-time feedback, but typically require substantial infrastructure, data management capacity, and technical support (Chen et al., 2020; Zawacki-Richter et al., 2019). In contrast, non-AI or moderately adaptive systems provide satisfactory learning outcomes with lower implementation complexity, making them more feasible for institutions with limited resources (Anand et al., 2026). Accordingly, system selection should align with institutional capacity, educational level requirements, and long-term strategic goals rather than technological sophistication alone (Ertmer & Ottenbreit-Leftwich, 2010).

Limitations and Future Research

This study focuses on literature published between 2022 and 2025, providing current insights but limiting historical perspective on long-term technological evolution. The concentration of studies in specific geographic contexts and potential publication bias toward positive outcomes may affect generalizability. In addition, the rapid evolution of AI-based technologies suggests that some conclusions may become outdated, underscoring the need for continuous updates.

Future research should address these limitations through longitudinal studies examining sustained effectiveness and scalability across educational levels. Cross-cultural validation studies are needed to enhance generalizability, while economic analyses of cost-effectiveness and return on investment could support policy and procurement decisions. Further investigation into emerging technologies such as virtual reality, augmented reality, and advanced natural language processing may extend system capabilities. As systems become more autonomous, research on ethics, data privacy, and algorithmic fairness will also be essential.

Additional research should address gaps in long-term effectiveness studies, primary education implementations, and affective outcome measurement. The concentration of research in higher education highlights the need for more studies in secondary and primary contexts. Cost-effectiveness analysis also remains largely absent and represents a critical gap for policy decisions.

CONCLUSION

This study synthesized evidence on adaptive learning systems in mathematics education to address implementation patterns, effectiveness, and challenges. Findings indicate that adaptive learning systems are widely implemented across educational levels and demonstrate consistent positive effects on performance, engagement, and conceptual understanding. However, their success depends strongly on pedagogical alignment, teacher preparedness, and institutional readiness. Overall, the findings suggest that effective adoption of adaptive learning systems requires not only technological advancement but also context-sensitive strategies integrating pedagogical and organizational dimensions.

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