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PAPER

AI-Driven Adaptive Learning Systems in Mobile Education: A Systematic Review of Personalization Strategies, Effectiveness, and User Interaction

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ABSTRACT

While artificial intelligence (AI) has transformed educational contexts through automated feedback generation, critical fragmentation exists in understanding its sustained impact on student learning trajectories, particularly regarding emotion recognition technologies in mobile STEM education. This systematic review investigates AI-driven adaptive learning systems in mobile education, examining personalization strategies, effectiveness measures, and user interaction patterns to establish foundations for emotion-aware educational technologies. A systematic literature review following PRISMA guidelines was conducted across major academic databases, yielding 39 eligible studies from 2015–2025. Bibliometric analysis using R Studio's bibliometric package examined research patterns, collaboration networks, and thematic evolution. Network analysis of key term co-occurrences and cluster analysis identified conceptual relationships and structural hierarchies within the research domain. The field demonstrates exponential growth with a 32.75% annual increase in research output, particularly since 2022. Mobile learning emerged as the dominant conceptual hub (betweenness centrality: 197.446), with AI and personalized learning serving as critical connectors between research domains. Three primary themes were identified: personalization strategies establishing sophisticated frameworks for learner modeling and context-aware adaptation; effectiveness measures revealing consistent improvements in academic performance and engagement across STEM contexts; and user interaction patterns exposing both transformative potential and challenges concerning data privacy and usability considerations. This study provides the first comprehensive systematic mapping of AI-driven mobile learning through the lens of emotion recognition potential, revealing substantial gaps in longitudinal impact assessment and theoretical integration. Findings advance understanding of how the Adaptive Feedback Regulation Framework can be enhanced through emotion-aware technologies, offering practical insights for implementing sophisticated personalization strategies. Future research should prioritize longitudinal studies examining sustained impact, cross-cultural acceptance patterns, and ethical implications of emotion recognition in educational contexts.

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KEYWORDS
artificial intelligence (AI), adaptive learning systems, mobile education, personalization strategies, systematic review, user interaction design

1 INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies across educational landscapes has fundamentally transformed how learners engage with educational content, particularly within mobile learning environments that offer unprecedented flexibility and accessibility [1]. Mobile learning, enhanced by AI-driven adaptive systems, has emerged as a critical educational paradigm that addresses the diverse needs of contemporary learners through personalized, context-aware, and responsive learning experiences [2], [3]. The integration of AI technologies in mobile education has demonstrated significant potential for enhancing academic performance, improving learning efficiency, and fostering individualized learning pathways that adapt to learners' dynamic behaviors and contextual factors [4], [5].

The significance of AI-driven mobile learning systems extends beyond mere technological innovation to address fundamental educational challenges, including accessibility, personalization, and scalability [6]. Recent studies have consistently shown that mobile learning platforms powered by AI can significantly improve learner experiences, leading to enhanced engagement, superior academic achievements, and more effective skill development across diverse educational contexts [7], [8]. The integration of machine learning algorithms, natural language processing, and adaptive assessment mechanisms has enabled educational systems to provide real-time, personalized feedback and support that adapts to individual learner characteristics, contextual information, and performance patterns [9], [10]. Furthermore, the cost-effectiveness and resource optimization capabilities of mobile learning platforms have made quality education more accessible while maintaining pedagogical effectiveness, particularly crucial for developing educational infrastructure in resource-constrained environments [11].

Despite the growing recognition of AI's transformative potential in mobile education, current research reveals significant limitations in understanding the sustained impact of these technologies on learning outcomes. Existing literature predominantly focuses on immediate efficacy measures of AI-generated feedback in enhancing engagement or performance, with studies examining short-term improvements in academic achievement and user satisfaction [12], [13]. However, contemporary research fails to capture the longitudinal effects of AI interventions on learning outcomes over extended periods, limiting our understanding of how these systems contribute to sustained learning retention and long-term educational benefits [14]. While studies have demonstrated that AI-driven systems can improve learning effectiveness through personalized support and adaptive content delivery, the temporal scope of these investigations remains constrained to immediate or short-term outcomes [15], [16]. While recent studies have begun investigating multimodal data analysis for cognitive load measurement and context-aware learning support, the integration of emotion recognition specifically within mobile STEM education remains underexplored [17].

Moreover, existing research demonstrates insufficient attention to critical user interaction dimensions, particularly concerning data privacy perceptions and user comfort levels in AI-enhanced learning systems. While studies have identified usability challenges and privacy concerns associated with AI-enabled mobile learning applications, comprehensive investigation of learner acceptance and emotional responses to advanced AI features, including emotion recognition capabilities, remains limited [18], [19]. This knowledge gap is particularly significant given the increasing sophistication of AI technologies that collect and analyze sensitive learner data, including emotional states, physiological responses, and behavioral patterns, which require careful consideration of ethical implications and user trust factors.

This research aims to comprehensively investigate the multifaceted impact of AI-driven emotion recognition on mobile adaptive learning systems within STEM education by examining both immediate and long-term effects on student learning outcomes. The study seeks to determine how real-time emotion recognition integration influences the effectiveness of personalization strategies, systematically measuring its contribution to student engagement, academic performance, and sustained learning retention. Furthermore, this study will analyze emerging user interaction patterns and learner preferences while exploring critical dimensions of data privacy perceptions and user comfort levels in emotion-aware adaptive learning systems, ultimately providing a holistic understanding of AI-driven personalization through the lens of the Adaptive Feedback Regulation Framework to bridge existing theoretical and empirical gaps in mobile STEM education.

2 MATERIALS AND METHODS

The systematic literature review adhered to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines to ensure methodological rigor and transparency in the selection process [20], [21]. Inclusion criteria encompassed peer-reviewed articles, book chapters, books, and review papers published in English that empirically examined the intersection of adaptive or personalized learning systems, mobile learning environments, and AI or machine learning technologies. Studies were required to focus on educational contexts with measurable outcomes related to learning effectiveness, user engagement, or system performance. Exclusion criteria eliminated conference abstracts, editorial comments, opinion pieces, and studies that examined AI in education without specific mobile learning components or those focusing solely on theoretical frameworks without empirical validation. Additionally, studies conducted in languages other than English, duplicate publications, and research primarily addressing technical implementation without educational impact assessment were excluded. The initial search yielded 72 records, which were subsequently filtered to 67 documents after subject area refinement across Computer Science, Social Sciences, Engineering, Mathematics, Decision Sciences, Energy, Multidisciplinary, Business Management and Accounting, and Economics Econometrics and Finance, ultimately resulting in 39 eligible documents after applying type and language restrictions. Figure 1 illustrates the inclusion and exclusion of articles.

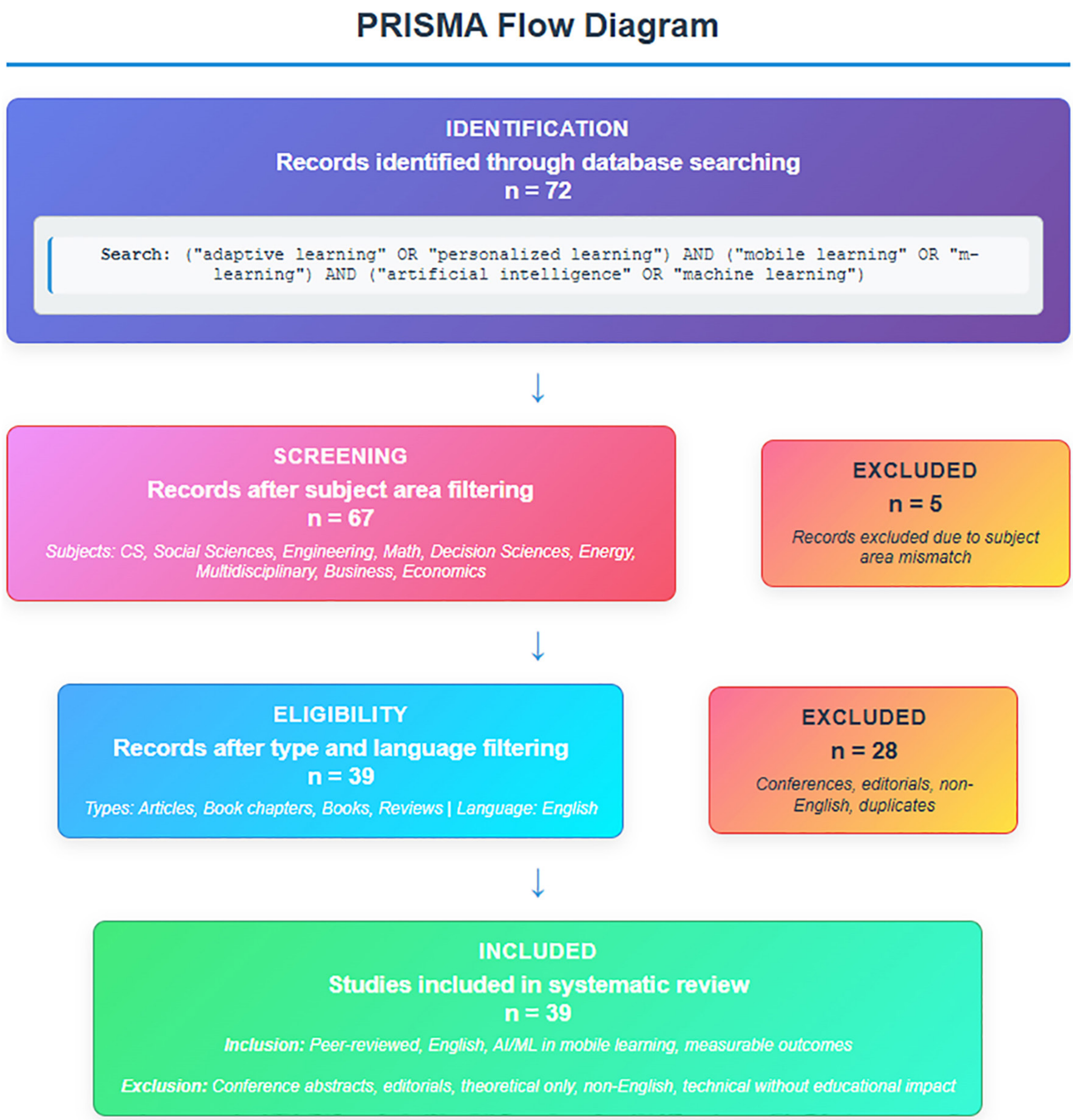

Fig. 1. PRISMA inclusion and exclusion of articles

3 RESULTS

3.1 Descriptives

Table 1 presents a comprehensive bibliometric analysis of the 39 documents identified through the systematic search, revealing key characteristics of the research landscape on AI-driven adaptive learning systems in mobile education. The dataset spans a decade from 2015 to 2025, encompassing 27 distinct sources, including journals and books, with an impressive annual growth rate of 32.75%, indicating rapidly expanding scholarly interest in this interdisciplinary field. The relatively low document average age of 1.51 years suggests that this study area is characterized by recent, cutting-edge publications, though the average citation count of 6.333 per document reflects the emerging nature of the field with citations still accumulating over time. The analysis reveals moderate collaborative patterns among the 110 contributing authors, with most documents (31 out of 39) being multi-authored, resulting in an average of 2.9 co-authors per document and international collaboration occurring in approximately one-fifth (20.51%) of the publications. The document type distribution demonstrates a strong preference for empirical research, with articles comprising the majority (30 documents), complemented by book chapters (5), books (2), and review papers (2), indicating a field primarily driven by original research rather than theoretical synthesis. The substantial number of author keywords (162) and Keywords Plus identifiers (198) alongside 1,667 references underscores the interdisciplinary nature and rich conceptual diversity characterizing this emerging research domain.

Table 1. Records information

Description	Results
Sources (Journals, Books, etc.)	27
Documents	39
Annual Growth Rate %	32.75
Document Average Age	1.51
Average citations per doc	6.333
References	1667
Keywords Plus (ID)	198
Author's Keywords (DE)	162
Authors	110
Authors of single-authored docs	7
Single-authored docs	8
Co-Authors per Doc	2.9
International co-authorships %	20.51
Article	30
Book	2
Book chapter	5
Review	2

In addition, Figure 2 of annual scientific production reveals a distinct evolutionary pattern in AI-driven adaptive learning systems research within mobile education, characterized by three distinct phases over the decade-long timespan from 2015 to 2025. The initial foundation period (2015–2021) demonstrates sporadic but persistent research activity with minimal annual output, reflecting the nascent stage of this interdisciplinary field where foundational concepts were being established.

A notable transition occurred in 2022–2023, marking the beginning of accelerated research interest, with publications increasing from one to four articles annually, suggesting growing recognition of the field's potential and technological feasibility. The most striking feature is the exponential surge in 2024–2025, where publications dramatically escalated from 10 to 18 articles, respectively, representing a 180% increase and validating the calculated annual growth rate of 32.75%. This exponential growth pattern indicates that the field has reached a critical maturity threshold, likely driven by advances in mobile computing capabilities, AI accessibility, and increased demand for personalized educational solutions, positioning AI-driven adaptive mobile learning as a rapidly expanding and increasingly significant research domain within educational technology.

Fig. 2. Annual productions of the articles

Furthermore, Figure 3 illustrates the distribution of publications across academic sources, revealing a highly concentrated publication pattern within the AI-driven adaptive learning systems in the mobile education research domain. The International Journal of Interactive Mobile Technologies emerges as the dominant publication venue, accounting for 10 out of 39 total documents (25.6%), establishing itself as the primary scholarly outlet for this interdisciplinary field and suggesting its specialized focus aligns closely with mobile learning technologies. The remaining publications demonstrate significant fragmentation across diverse academic sources, with four journals each contributing two articles: *Educational Process: International Journal*, *IEEE Access*, *Sustainability (Switzerland)*, and *British Journal of Educational Technology*, collectively representing 20.5% of the corpus. The distribution further extends across six additional sources, each contributing a single publication, including specialized venues such as *Computers and Education: Artificial Intelligence* and *Frontiers in Education*, as well as edited volumes focusing on smart pedagogy and educational technology integration. This publication pattern indicates that while the *International Journal of Interactive Mobile Technologies* serves as the field's primary knowledge repository, the research area maintains strong interdisciplinary characteristics, spanning computer science, education, sustainability, and technology-enhanced learning domains, reflecting the inherently multifaceted nature of AI-driven mobile education research.

Fig. 3. Most relevant sources

3.2 Bibliometric analysis

The bibliometric analysis was conducted using R Studio, leveraging the comprehensive capabilities of the bibliometric package [22], which provides robust tools for quantitative analysis of scientific literature and enables systematic examination of research patterns, collaboration networks, and knowledge evolution within academic domains. Figure 4 presents a word cloud visualization of the most frequently occurring terms within the AI-driven adaptive learning systems in the mobile education research corpus, revealing the dominant conceptual landscape and thematic priorities of the field. The visualization is hierarchically structured with "mobile learning" and "artificial intelligence" appearing as the largest terms, confirming these as the central pillars of the research domain, while "personalized learning," "federated learning," "machine learning," and "adversarial" emerge as secondary but substantial concepts, indicating the field's focus on individualized educational approaches and advanced AI methodologies.

The prominence of terms such as "contrastive learning," "e-learning," "learning systems," and "adaptive learning" demonstrates the technical sophistication and pedagogical foundations underlying current research, while smaller but visible terms such as "transfer learning," "self-supervised learning," "generative artificial intelligence," and "higher education" suggest emerging trends and application contexts. This lexical distribution illustrates that the field maintains a balanced emphasis between technological innovation (machine learning, AI techniques) and educational application (personalized learning, mobile platforms), with the word cloud effectively capturing the interdisciplinary nature of research that bridges computer science methodologies with educational technology implementation, ultimately reflecting a mature research area that encompasses both foundational concepts and cutting-edge developments in intelligent mobile learning systems.

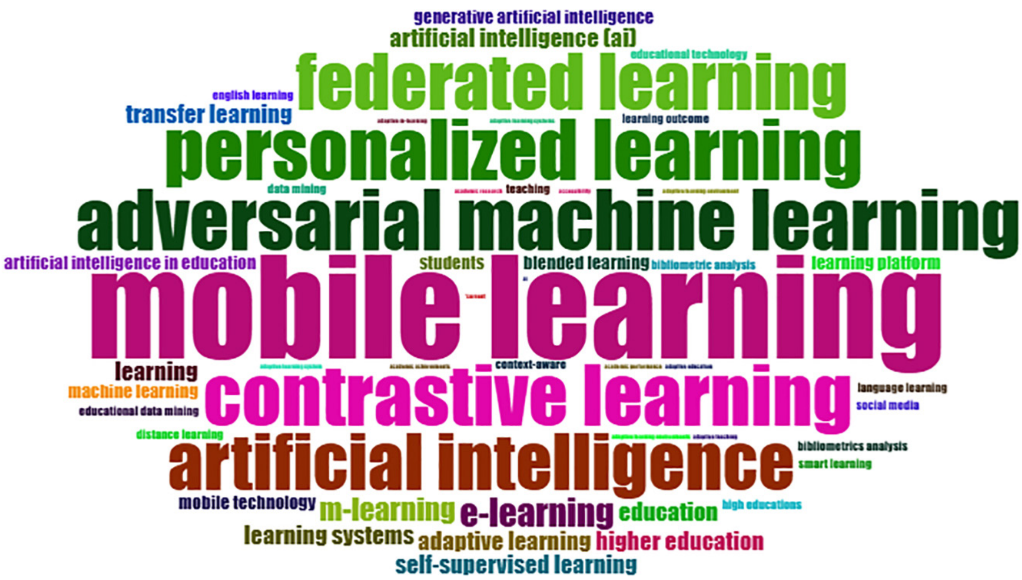

Fig. 4. Word cloud of most frequent words

Co-occurrences of key terms. Table 2 presents network analysis metrics for key terms in AI-driven adaptive learning systems research, revealing distinct patterns of conceptual connectivity and influence within the research domain. Mobile learning emerges as the most central and influential concept with the highest betweenness centrality (197.446), closeness centrality (0.019), and PageRank score (0.112), establishing it as the primary bridge connecting different research themes and the most accessible concept within the network structure. AI (101.289 betweenness, 0.073 PageRank) and personalized learning (76.168 betweenness, 0.08 PageRank) demonstrate substantial intermediary roles, indicating their function as key connectors between disparate research areas, while advanced AI techniques such as contrastive learning (38.119 betweenness) and adversarial machine learning (23.439 betweenness) show moderate bridging capabilities despite their specialized nature. Notably, many fundamental educational concepts, including adaptive learning, machine learning, and education itself, exhibit zero betweenness centrality, suggesting they operate as endpoint concepts rather than connective hubs, while federated learning demonstrates surprising network influence (19.415 betweenness, 0.082 PageRank) relative to its specialized application domain, indicating its emerging importance in connecting mobile learning with distributed AI methodologies.

Table 2. Key terms occurrence

Key Term	Betweenness Centrality	Closeness Centrality	PageRank Score	Network Role
Mobile Learning	197.446	0.019	0.112	Primary Hub
Artificial Intelligence	101.289	0.015	0.073	Major Connector
Personalized Learning	76.168	0.017	0.08	Bridge Concept
Contrastive Learning	38.119	0.015	0.067	Specialized Bridge
Adversarial Machine Learning	23.439	0.015	0.076	Technical Connector
Federated Learning	19.415	0.015	0.082	Emerging Hub
E-learning	10.913	0.014	0.034	Secondary Bridge
Learning Systems	3.81	0.013	0.03	Minor Connector
Artificial Intelligence (AI)	0.78	0.014	0.035	Peripheral Node
Students	0.301	0.011	0.018	Peripheral Node

In addition, Figure 5 presents a network visualization that corroborates the quantitative findings from Table 2, illustrating the conceptual relationships and structural hierarchy within AI-driven adaptive learning systems research. The network diagram confirms mobile learning as the dominant central hub, represented by the largest node with extensive connectivity to multiple research domains, visually reinforcing its highest betweenness centrality score of 197.446. The visualization clearly demonstrates the bridging roles of AI, personalized learning, and contrastive learning through their strategic positioning and multiple connections, while advanced AI techniques such as federated learning, adversarial machine learning, and self-supervised learning form a distinct cluster in the upper region, indicating their interconnected yet specialized nature within the broader research ecosystem. The spatial arrangement reveals three primary thematic clusters: a core mobile learning hub connected to fundamental educational concepts (e-learning, blended learning, adaptive learning), an AI-technical cluster encompassing advanced machine learning methodologies, and a peripheral educational context cluster including higher education and teaching applications. This network topology validates the centrality metrics by visually demonstrating how mobile learning serves as the primary connector between diverse research themes, while concepts with zero betweenness centrality appear as terminal nodes with limited cross-domain connectivity, effectively mapping the intellectual structure and knowledge flow patterns within this interdisciplinary research field.

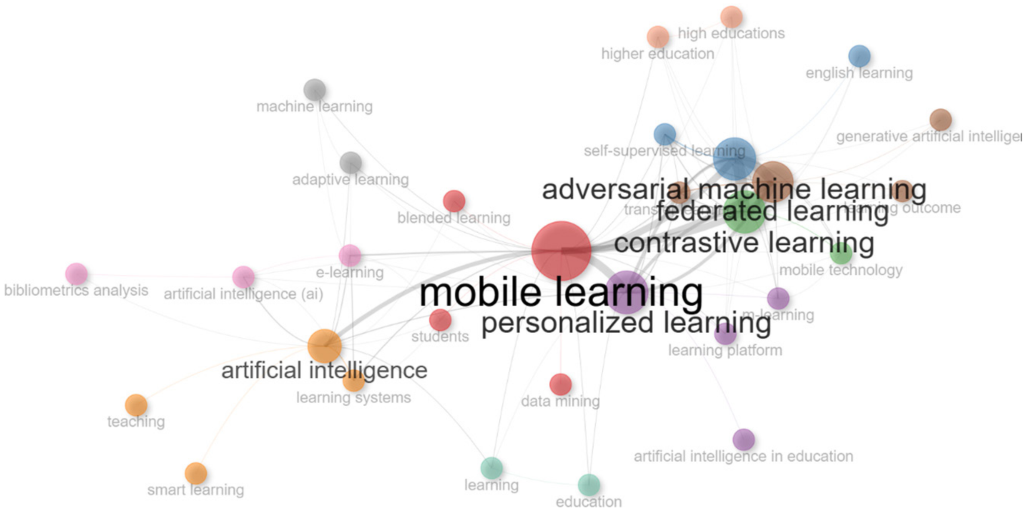

Fig. 5. Co-occurrence network

Themes identification. Table 3 presents cluster analysis metrics that reveal distinct thematic groupings within the AI-driven adaptive learning systems research network, with four primary clusters demonstrating varying levels of centrality and internal cohesion. The mobile learning cluster emerges as the most prominent with the highest Callon centrality (3.048) and density (74.018), ranking fourth in both metrics while encompassing the largest frequency of 121 terms, indicating its role as the most developed and internally connected research domain. The AI cluster demonstrates moderate centrality (2.536) with substantial density (50.198) and a frequency of 36 terms, positioning it as a well-established but more specialized research area, while the education cluster shows lower centrality (1.271) but higher density (60.714) with 18 terms, suggesting a cohesive but less central thematic focus. The educational data mining cluster appears as the most peripheral with zero centrality and moderate density (50), containing only 2 terms, indicating its emerging or highly specialized nature within the research landscape.

Table 3. Clusters metrics

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
artificial intelligence	2.536	50.198	3	2	36
education	1.271	60.714	2	3	18
mobile learning	3.048	74.018	4	4	121
educational data mining	0	50	1	1	2

In addition, Figure 6 visually corroborates these quantitative findings through a color-coded network visualization that clearly delineates the four clusters, with the mobile learning cluster (green) dominating the central region and demonstrating extensive inter-cluster connectivity, the AI cluster (red) forming a substantial secondary hub with strong internal linkages, and the education cluster (blue) appearing as a cohesive but peripheral grouping. The spatial arrangement confirms the centrality rankings from Table 3, as the mobile learning cluster occupies the most central network position with dense interconnections, while the educational data mining cluster appears as isolated peripheral nodes, effectively illustrating the structural hierarchy and thematic organization of knowledge domains within AI-driven mobile education research.

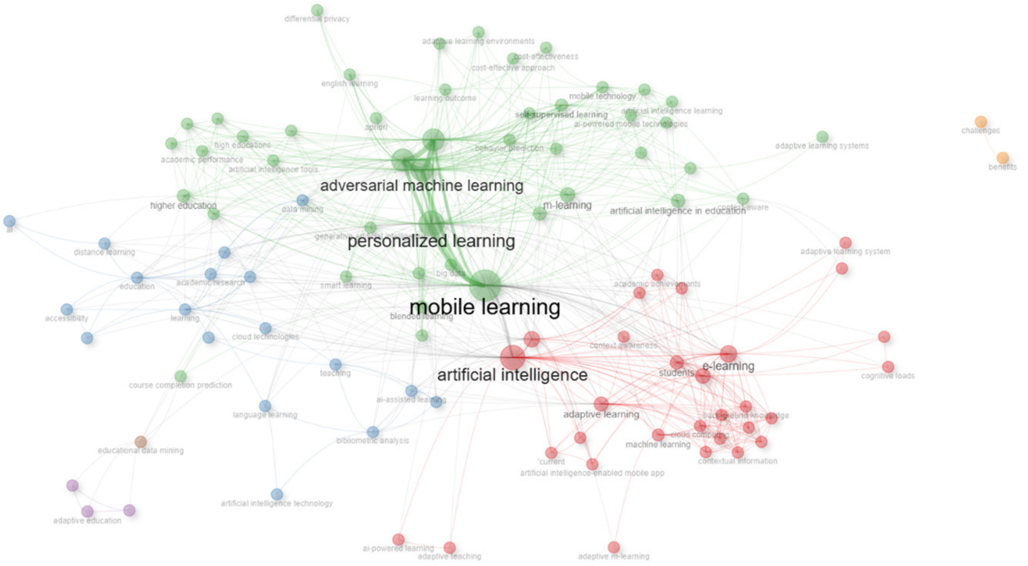

Fig. 6. Clusters network

3.3 Thematic classification

The comprehensive analysis of AI-driven adaptive learning systems in mobile education reveals three interconnected themes that directly address the research objectives of investigating emotion recognition's impact on personalization strategies, effectiveness, and user interaction patterns within STEM education contexts.

Personalization strategies: The foundation of emotion-aware adaptive learning. The first theme establishes the critical foundation for understanding how AI-driven emotion recognition can enhance personalization strategies in mobile adaptive learning systems. Contemporary research demonstrates that adaptive learning paths and content represent the cornerstone of effective personalization, with systems creating flexible pathways that adjust to diverse learner behaviors and contextual factors [23]. This aligns with the research objective of determining how real-time emotion recognition influences personalization effectiveness, as learner modeling techniques utilizing DBSCAN and K-means clustering algorithms successfully classify learners based on behavioral, contextual, and emotional factors to deliver personalized content within structured course ontologies [24].

The integration of data-driven customization approaches further supports the research aims by demonstrating how mining techniques, including K-means clustering and time series analysis, identify students' learning behavior characteristics and emotional changes, providing foundations for designing personalized learning paths [4]. Particularly relevant to STEM education contexts, context-aware learning systems extract learners' contextual information from mobile devices, enabling real-time adaptive support that accounts for external factors such as noise level, physical activity, and location that significantly impact learner concentration [9]. This contextual awareness directly supports the research objective of analyzing user interaction patterns, as emotion recognition systems can leverage similar environmental and physiological data to enhance personalization strategies.

The emergence of AI as a personal assistant through chatbot applications and generative AI integration provides a direct pathway for implementing emotion-aware systems, facilitating personalized learning experiences through real-time feedback and support [7], [25]. These findings suggest that emotion recognition technologies can seamlessly integrate into existing personalization frameworks, enhancing the Adaptive Feedback Regulation Framework by incorporating emotional states as key variables in adaptive decision-making processes.

Effectiveness: Measurable impacts on learning outcomes and engagement. The second theme directly addresses the research objective of measuring AI-driven systems' contribution to student engagement, academic performance, and sustained learning retention. Research consistently demonstrates that AI-driven mobile learning systems significantly improve learner experiences, leading to enhanced academic performance and learning outcomes with statistically significant improvements in student performance across various STEM domains [5]. The integration of AI in mobile learning has proven to enhance learning effectiveness through personalized support, with studies showing substantial improvements in programming skills when AI-integrated platforms provide personalized assistance and real-time debugging support [8].

Improved efficiency and engagement represent a critical outcome measure for emotion-aware systems, with optimization strategies based on data mining demonstrating improved learning effectiveness for both teachers and platform developers [4]. The flexibility and accessibility of mobile learning platforms enable meaningful tailoring of learning processes, while AI-integrated systems offer personalized assistance that significantly enhances programming skills and vocabulary acquisition [16], [26]. These findings support the research objective of examining sustained learning retention, as personalized mobile learning environments demonstrate superior academic achievements compared to traditional approaches.

The emphasis on specific skill development particularly relevant to STEM education shows AI technology's effectiveness in maximizing language learning preparation and developing technical skills through personalized feedback and assessment capabilities [25]. Resource optimization and cost-effectiveness further support the practical implementation of emotion-aware systems, with mobile learning achieving significant cost savings while maintaining educational quality [11]. Importantly, research on cognitive load management demonstrates that machine learning approaches can predict learners' real-time cognitive load through multimodal data analysis, directly supporting the integration of emotion recognition technologies for optimizing adaptive learning systems [7].

User interaction: Privacy, usability, and emotional considerations. The third theme comprehensively addresses the research objectives concerning user interaction patterns, learner preferences, and critical data privacy dimensions in emotion-aware adaptive learning systems. Interactive learning environments enable learners to actively engage with AI mentors through seamlessly integrated chat interfaces, receiving real-time feedback and support within dynamic environments that emphasize interaction and collaboration [27]. These systems' resilience and interaction capabilities can be enhanced through multi-agent system modeling, providing frameworks for implementing emotion recognition technologies that respond to complex user interaction patterns.

Usability and user experience considerations reveal critical challenges for emotion-aware systems, as while users generally report positive experiences with AI-enabled mobile learning applications, the integration of AI introduces usability issues related to functionality, performance, potential bias, explanation of AI decisions, and feature effectiveness [18]. These findings directly inform the research objective of exploring user comfort levels in emotion-aware systems, highlighting the need for developers to address usability concerns while implementing emotion recognition capabilities that enhance rather than complicate user experiences.

Data collection and privacy concerns represent perhaps the most critical consideration for emotion recognition systems, as dynamic user profiling based on mobile usage data inherently raises privacy concerns that must be addressed through differential privacy and secure multi-party computation solutions [15]. The ethical implications of collecting and using student data, particularly emotional and physiological data, require vigilant consideration when incorporating emotion recognition technologies into educational settings [3]. This directly addresses the research objective of exploring data privacy perceptions, as successful implementation of emotion-aware systems depends on building user trust through transparent and secure data handling practices.

Perceptions and sentiments regarding AI applications in education reflect a duality of emotions, with prevalent positive feelings such as 'trust' and 'joy' concerning AI's potential to enhance efficiency and education, alongside negative emotions such as 'fear' stemming from concerns about job displacement and impacts on human creativity [19]. Measuring learner behavior through advanced methods employing time series analysis and smartphone sensor data provides foundations for implementing emotion recognition systems that track students' emotional changes and learning progress, supporting personalized learning path design [26]. The consideration of context adaptation based on device characteristics ensures that emotion-aware systems optimize experiences according to mobile device capabilities, supporting the holistic implementation of adaptive learning technologies within the Adaptive Feedback Regulation Framework. Table 4 illustrates the studies discussed about AI-driven mobile learning in the current study.

Table 4. Summary of studies in AI-driven mobile learning thematic analysis

Author(s) & Year	Research Focus	Research Settings
El Ghouch & Mahboub (2025)	Adaptive learning system using dynamic case-based reasoning	Mobile learning environments
El Fezazi et al. (2025)	AI-driven Moodle plugin for personalized M-learning	Higher education – Ibn Tofail University
Zhao & Teng (2025)	Data mining optimization for English learning on mobile platforms	Mobile learning platforms
Ayyal Awwad (2023)	Universal design for adaptive context-aware mobile cloud learning	Mobile cloud learning framework
Adnan et al. (2019)	Cloud-supported machine learning for context-aware M-learning	Computer programming education
Lubis et al. (2024)	AI technology utilization in language learning	Language learning contexts
Liu (2025)	Generative AI and mobile learning impact on employability	Higher education
Baba et al. (2024)	AI-driven personalized learning platform for mobile devices	Mohammed VI Polytechnic University
Atta et al. (2025)	ChatGPT mobile application for programming skills	Educational institutions – C# programming
Almogren et al. (2024)	Mobile learning, social media, and AI integration	Higher education – King Saud University
Higashimura et al. (2024)	Smartphone-based unknown English word estimation	English vocabulary learning
Suresh Kumar et al. (2024)	Cost-effective approach to mobile learning	M-learning environments
Li et al. (2024)	Cognitive load measurement in pen-based mobile learning	Mobile learning with multimodal data
Syed Ali & Kuotian (2024)	Personalized education via mobile technology frameworks	Mobile learning platforms
Alsanousi et al. (2023)	User experience evaluation in AI-enabled learning apps	Mobile learning applications
Wang (2025)	Privacy-preserving recommendation systems for English learning	Mobile learning with differential privacy
Petrakieva & McArthur (2019)	Mobile technologies and learning expectations	Mobile learning pedagogy
Stracqualursi & Agati (2024)	Public perceptions of AI-based e-learning technologies	Social media sentiment analysis

These findings collectively demonstrate that while emotion recognition technologies offer significant potential for enhancing personalization strategies, effectiveness measures, and user interactions in mobile STEM education, their successful implementation requires careful attention to privacy concerns, usability considerations, and ethical implications to achieve the research objectives of providing holistic understanding of AI-driven personalization in educational contexts.

4 CONCLUSION

This systematic review has successfully mapped the evolving landscape of AI-driven adaptive learning systems in mobile education, revealing a field experiencing exponential growth with a 32.75% annual increase in research output, particularly since 2022. Through comprehensive bibliometric analysis of 39 studies spanning 2015–2025 and employing network analysis of key term co-occurrences, this investigation has identified three fundamental themes that illuminate the current state and future potential of emotion recognition technologies within mobile STEM education contexts. The methodological approach utilizing PRISMA guidelines and R Studio's bibliometric package has provided robust insights into research patterns, collaboration networks, and thematic evolution within this interdisciplinary domain. Network analysis revealed mobile learning as the dominant conceptual hub (betweenness centrality: 197.446), with AI and personalized learning serving as critical connectors between research domains, while advanced AI techniques such as federated learning and contrastive learning emerge as specialized bridges within the knowledge ecosystem.

The analysis demonstrates that personalization strategies form the foundational architecture for implementing emotion-aware adaptive systems, with current research establishing sophisticated frameworks for learner modeling, context-aware adaptation, and data-driven customization that can readily accommodate emotion recognition technologies. The effectiveness theme reveals consistent evidence of improved academic performance, enhanced engagement, and superior learning outcomes across diverse STEM contexts, with studies showing statistically significant improvements when AI-driven personalization strategies are implemented. Critically, the user interaction theme exposes both the transformative potential and inherent challenges of emotion-aware systems, particularly concerning data privacy, usability considerations, and the complex emotional landscape surrounding AI acceptance in educational contexts.

This study contributes significantly to existing knowledge by providing the first comprehensive systematic mapping of AI-driven mobile learning research through the lens of emotion recognition potential, bridging theoretical frameworks with empirical evidence while revealing substantial gaps in longitudinal impact assessment and theoretical integration. The findings advance our understanding of how the Adaptive Feedback Regulation Framework can be enhanced through emotion-aware technologies, offering practical insights for educators, developers, and policymakers seeking to implement sophisticated personalization strategies in mobile STEM education. The study acknowledges limitations inherent in the systematic review methodology, including the focus on English-language publications and the relatively recent emergence of the field resulting in limited long-term impact studies. Additionally, the temporal scope constraint to 2015–2025 may have excluded foundational work that predates the mobile learning revolution.

Future research should prioritize longitudinal studies examining the sustained impact of emotion recognition technologies on learning retention and academic achievement over extended periods. Investigation of cross-cultural acceptance patterns for emotion-aware learning systems represents a critical research gap, particularly given the global nature of mobile education. Furthermore, empirical validation of the enhanced Adaptive Feedback Regulation Framework incorporating emotional states as key variables requires systematic experimental investigation. Research examining the ethical implications and optimal privacy-preserving mechanisms for emotion recognition in educational contexts emerges as an urgent priority, alongside studies exploring the integration of multimodal emotion detection technologies with existing mobile learning platforms. These research directions will be essential for realizing the transformative potential of emotion-aware adaptive learning systems while addressing the complex challenges surrounding privacy, usability, and user acceptance in mobile STEM education.

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