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PAPER

Explainable AI for Mobile Learning: Enhancing Trust and Transparency through HCI

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ABSTRACT

The digital transformation of education, driven by artificial intelligence (AI), has led to intelligent learning systems that personalize instruction, predict student performance, and automate assessments. However, the lack of transparency in AI-driven educational tools raises concerns about trust and user acceptance, particularly in mobile and interactive learning platforms used on-the-go by diverse users. Human-computer interaction (HCI) principles address these issues by promoting user-centered design and interpretability, aligning with pedagogical goals. Explainable AI (XAI) enhances this by making AI decisions understandable to educators and students. This study reviews the intersection of AI, HCI, and XAI in mobile learning, analyzing HCI's role in interface design, AI methodologies in adaptive environments, and XAI techniques for transparency. Findings highlight XAI's benefits in trust and accountability, alongside challenges like interpretability trade-offs, privacy, and mobile deployment costs. A research agenda is proposed to address these gaps, emphasizing ethical, transparent, and user-centric AI systems.

KEYWORDS

explainable AI (XAI), mobile learning, human-computer interaction (HCI), artificial intelligence (AI), transparency, trust, education technology, adaptive learning, user-centered design, privacy, ethical AI, machine learning (ML), interactive learning, mobile interfaces

1 INTRODUCTION

Digital transformation in education has become a priority worldwide, propelled by widespread smartphone adoption, online learning platforms, and interactive software. The integration of artificial intelligence (AI) into mobile educational technology has enhanced adaptive instruction, outcome prediction, and personalized content delivery [11, 12]. Beyond AI, augmented reality (AR) is emerging as a tool to enhance interactive learning experiences in mobile environments, addressing engagement challenges in traditional e-learning [80]. Although AI systems can significantly automate and optimize learning processes, they often act as "black boxes," making it difficult for educators, students, and administrators to fully trust

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or comprehend machine-driven outcomes [13]. A recent study [78] highlights that teachers' attitudes toward adopting AR in K-12 education vary significantly across cultural contexts, underscoring the need for transparent and user-centric designs in mobile learning technologies. In Arabic countries, research indicates a growing adoption of AI in mobile learning environments, with a notable shift toward personalized and resilient educational practices since 2018 [79].

Human-computer interaction (HCI) addresses these user-centric concerns, shaping the design of mobile learning technologies to meet learners' cognitive and socio-emotional needs [14]. Recently, a confluence of HCI and AI has emerged to address the transparency and trustworthiness of mobile intelligent systems in real-world educational contexts. Explainable AI (XAI) specifically aims to provide human-understandable justifications for AI decisions [15]. This is particularly important in education, as teachers and students need clear explanations about AI recommendations and evaluations in mobile learning.

Contributions and Objectives. This paper presents a systematic review of the research on HCI, AI, and XAI within educational settings with particular emphasis on mobile and interactive learning technologies. The goals are:

a) To identify the role of HCI in designing user-centered mobile educational interfaces.
b) To review key concepts and methodologies in AI that underpin modern adaptive mobile learning environments.
c) To analyze existing XAI techniques and how they enhance transparency and trust in AI-driven mobile educational tools.
d) To investigate how XAI can be harnessed to address challenges like student motivation, accessibility, and ethical use of AI in mobile education.
e) To present open issues and recommendations for future research in XAI for interactive and mobile learning.

A recent study [7] shows that students in the humanities and social sciences are more likely to adopt AI educational applications if they provide clear explanations, highlighting the importance of XAI in mobile contexts where technical constraints, such as battery limitations and intermittent connectivity, require optimized solutions. This paper places particular emphasis on these challenges specific to mobile platforms to ensure that intelligent systems remain accessible and effective in diverse learning environments.

The remainder of this paper is structured as follows: Section 2 outlines the systematic review approach, including explicit ethical considerations and methodological transparency. Section 3 discusses HCL and AI foundations. Section 4 examines the main characteristics of machine learning (ML) relevant to mobile education. Section 5 explores the intersection of HCI and AI, leading into the concept of XAI and its techniques in Section 6. Section 7 focuses on the applications and challenges of XAI within mobile/interactive education. Finally, Sections 9 and 10 provide conclusions and propose directions for future research.

2 METHODOLOGY OF THE REVIEW

This systematic literature review (SLR) examines the intersection of HCI, AI, and XAI in mobile and interactive education, following the PRISMA 2020 guidelines [10] and Okoli's SLR framework [9] for rigor and transparency. Spanning 2019–2024, the review captures recent advancements in explainability, justified by the post-2018 surge in XAI research following DARPA's program launch [15]. The process involved keyword searches, systematic screening, and data synthesis, detailed below.

2.1 Research questions

Aligned with the objectives stated in the introduction, we formulated the following research questions:

(RQ1) What are the challenges in HCI when developing **mobile** educational software interfaces?
(RQ2) Which ML techniques are widely applied to solve educational problems, and how do their key characteristics—like transparency and fairness—affect mobile users?
(RQ3) What are the prevalent approaches in XAI relevant to mobile education, and how are they validated?
(RQ4) What are the open problems and future research directions for implementing XAI in interactive and mobile learning environments?

2.2 Search strategy and data sources

Following the procedures outlined by [9] and updated PRISMA guidelines [10], we used combinations of keywords, including *"HCI," "Human-Computer Interaction," "Explainable Artificial Intelligence," "XAI," "mobile learning," "interactive learning," "Machine Learning," "Adaptive Learning," "User-Centered Design,"* and *"Transparency in AI."*

Searches were conducted across multiple academic databases to maximize coverage. Although databases such as IEEE, ACM, ScienceDirect, and SpringerLink are reputable, this selection might introduce potential bias by underrepresenting regional studies from developing countries or publications from open-access repositories. Future reviews could include databases such as ERIC or open-access sources such as arXiv to ensure a more globally inclusive perspective.

- Google Scholar
- IEEE Xplore
- ACM Digital Library
- ScienceDirect
- SpringerLink

We limited our search to peer-reviewed articles, conference proceedings, and published book chapters from 2019 to 2024 to capture the most current developments in these rapidly evolving fields [6]. The methodology rigorously followed PRISMA guidelines. We justified the selection period (2019–2024) by referencing key milestones such as the DARPA XAI program launched in 2018, marking significant growth and increased research in explainability techniques. A systematic screening process was then carried out, involving duplicate removal, title/abstract inspection, and full-text evaluation. Articles that did not address the intersection of HCI, ML, or XAI within mobile or interactive educational settings, or that lacked empirical or theoretical contributions, were excluded.

Table 1. AI in education data sources

Data Source	Description	Relevance to AI in Education
Google Scholar	A freely accessible search engine that indexes scholarly articles from various disciplines.	Contains a vast number of AI-related papers, including explainability and mobile HCI studies.
IEEE Xplore	A digital library for research papers in electrical engineering, computer science, and related fields.	Provides high-quality peer-reviewed papers on AI methodologies and their applications in mobile.
ACM Digital Library	A comprehensive database for computing and information technology research.	Focuses on AI, human-computer interaction, and software-based educational research, including mobile apps.
ScienceDirect	A scientific database covering a wide range of academic disciplines, including AI and education.	Offers access to interdisciplinary research on AI-driven mobile education and pedagogy.
SpringerLink	An academic publisher providing access to journals and conference proceedings in multiple fields.	Includes key journals and conference proceedings relevant to AI-driven and XAI-based mobile learning.

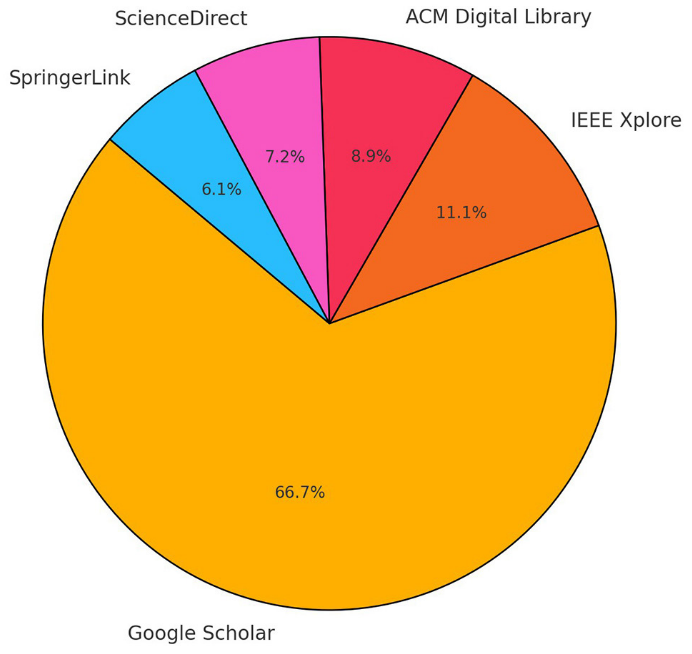

Fig. 1. Distribution of AI and XAI articles (2019–2024) by database

2.3 Inclusion and exclusion criteria

Inclusion Criteria:

- Papers published from 2019 onward to capture the recent surge in XAI research.
- Studies discussing AI-based educational tools with a mobile or interactive learning component.
- Peer-reviewed journal articles, conference proceedings, and relevant review articles.

Exclusion Criteria:

- Non-English publications.
- Studies focusing solely on healthcare or industry applications without any educational or mobile/interactive perspective.
- Duplicated or incomplete papers.
- Grey literature (preprints, white papers, or industry reports) was deliberately excluded from this review due to concerns regarding the quality assurance and peer-review process, potentially affecting the reliability of the synthesized findings.

Justification of Inclusion/Exclusion Criteria:

- **Why choose 2019 as the starting point?** XAI underwent rapid development after 2018, with a significant expansion of interpretability techniques across various domains, including mobile education.
- Mobile/Interactive Filter: We specifically filtered for studies that examined how AI or XAI is implemented or tested on smartphones, tablets, or other interactive learning interfaces.

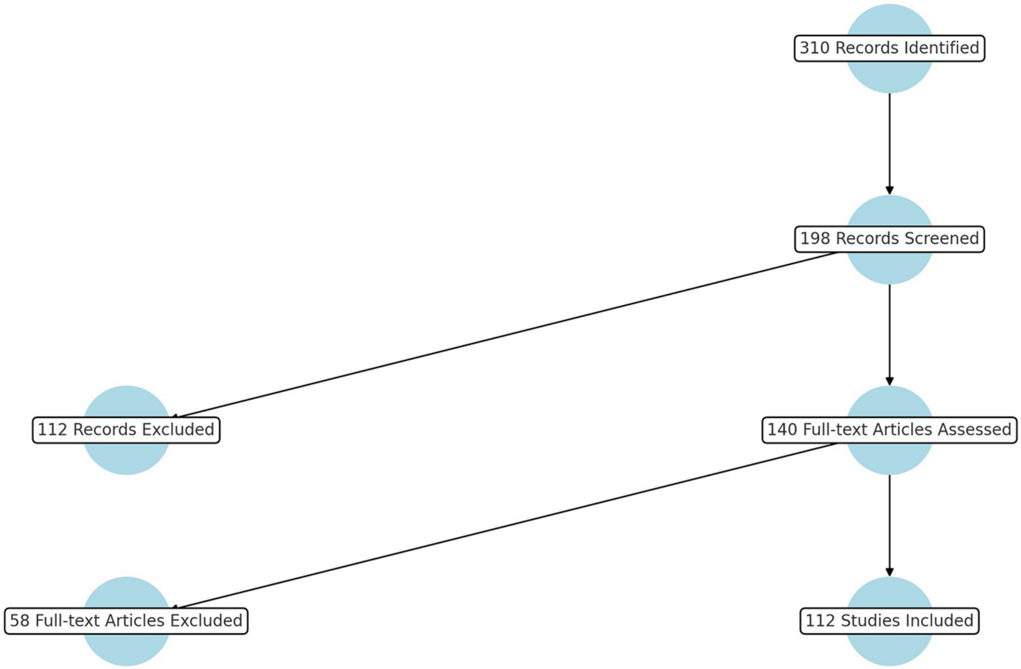

Fig. 2. PRISMA flow diagram: Number of records included and excluded

2.4 Ethical approval statement

This systematic review does not involve direct human participants, as no primary data collection was conducted. However, included studies involving human subjects adhere to recognized ethical standards, such as the Declaration of Helsinki. Beyond this, the deployment of XAI in mobile learning raises ethical implications, including data privacy risks from student usage analytics, potential algorithmic bias in AI recommendations, and the need for transparency to ensure trust among users.

These concerns are further explored in Section 7, emphasizing their relevance to responsible AI adoption in education.

2.5 Review process

Titles and abstracts were initially screened to remove unrelated papers. Full texts of the remaining articles were subsequently reviewed. Key findings were tabulated under: (1) study context, (2) AI/HCI methods, (3) XAI techniques, (4) mobile/interactive aspects, and (5) limitations/gaps.

3 BACKGROUND OF RESEARCH

This section highlights core foundations of HCI and AI, underscoring their relevance in shaping mobile and interactive educational technologies.

3.1 HCI in education

Human-computer interaction focuses on creating effective dialogues between humans and computers [16]. In mobile education, HCI principles ensure that apps, e-textbooks, and interactive simulations are accessible, engaging, and aligned with student needs [14].

A recent article [7] identifies transparency as a key determinant of students' intention to use AI in academic contexts, a critical factor for mobile applications where trust is essential due to limited interfaces and brief interactions. This observation underscores the necessity of integrating XAI to meet user expectations in digital educational environments.

1. **Usability in Mobile Settings:** Usability is a critical determinant of the effectiveness of AI-driven mobile educational systems, ensuring that students, educators, and administrators can efficiently interact with these technologies on small screens. The classic metrics (effectiveness, efficiency, and satisfaction) remain crucial but are adapted to shorter interaction times, on-the-go usage, and potentially limited device capabilities. The usability of AI-based educational tools can be quantitatively assessed through key metrics, as defined by international standards such as ISO 9241.

   Key Metrics for Usability Evaluation: The usability of AI-driven educational systems is measured through three primary metrics: effectiveness, efficiency, and satisfaction. These metrics provide a mathematical framework for assessing the interaction between users and the system.

   Effectiveness: Effectiveness measures the extent to which users can achieve specified learning goals using the system. It is calculated as:

$$Effectiveness = \left(\frac{T_s}{T_t}\right) \times 100 \quad (1)$$

   where:
   - T_s = Number of successfully completed tasks,
   - T_t = Total number of tasks attempted.

   A higher effectiveness score indicates a system that enables users to complete their learning objectives with minimal difficulties.

Efficiency: Efficiency evaluates the time required by users to complete a task relative to the expected duration. It is computed as:

$$Efficiency = \frac{\sum_{i=1}^{N}\sum_{j=1}^{R}\frac{n_{ij}}{t_{ij}}}{NR} \quad (2)$$

where

- N = Total number of tasks,
- R = Number of users,
- n_{ij} = Completion status of task i by user j (1 if completed, 0 if not), and
- t_{ij} = Time taken by user j to complete task i (in seconds).

Higher efficiency values indicate that users can perform tasks in a shorter time frame, reflecting better system usability.

Satisfaction: Satisfaction is a subjective measure derived from user feedback on the overall experience with the system. It is expressed as:

$$Satisfaction\ Rate = \left(\frac{S + (U \times 0.5)}{P}\right) \times 100 \quad (3)$$

where

- S = Number of successful attempts,
- U = Total number of users, and
- P = Total number of tasks performed.

Higher satisfaction scores indicate a positive user experience, which is essential for AI-based educational systems to gain user trust and widespread adoption.

2. **Human-Centered Design (HCD):** is a user-focused methodology that ensures AI-driven educational systems are designed iteratively to meet the cognitive and pedagogical needs of learners and instructors. This approach incorporates:
   - **Iterative User Research:** Conducting frequent user studies to understand students' and teachers' needs.
   - **Prototyping:** Developing and refining system prototypes to enhance usability before full implementation.
   - **User Testing:** Employing usability testing methods to gather feedback and optimize system design.
   - **Personalization:** Tailoring AI interactions based on user preferences and learning behaviors to maximize engagement.

Human-centered design ensures that AI-driven learning technologies remain intuitive, effective, and adaptable, thereby improving overall usability and adoption in educational settings.

3.2 AI in education

AI has revolutionized many domains, including education, by enabling intelligent systems capable of classification, prediction, decision-making, and problem-solving [17]. These systems often surpass human-level performance in specific tasks, offering enhanced personalization and automation in mobile-first learning environments.

- **Machine Learning (ML):** Critical in adaptive learning, automated assessment, and real-time performance prediction on mobile devices.
- **Deep Learning (DL):** Effective for complex tasks like automated feedback on essays or voice-based coaching in language apps [18].
- **Natural Language Processing (NLP):** Enables chatbots and real-time text or speech feedback, essential for on-the-go mobile learning [19].

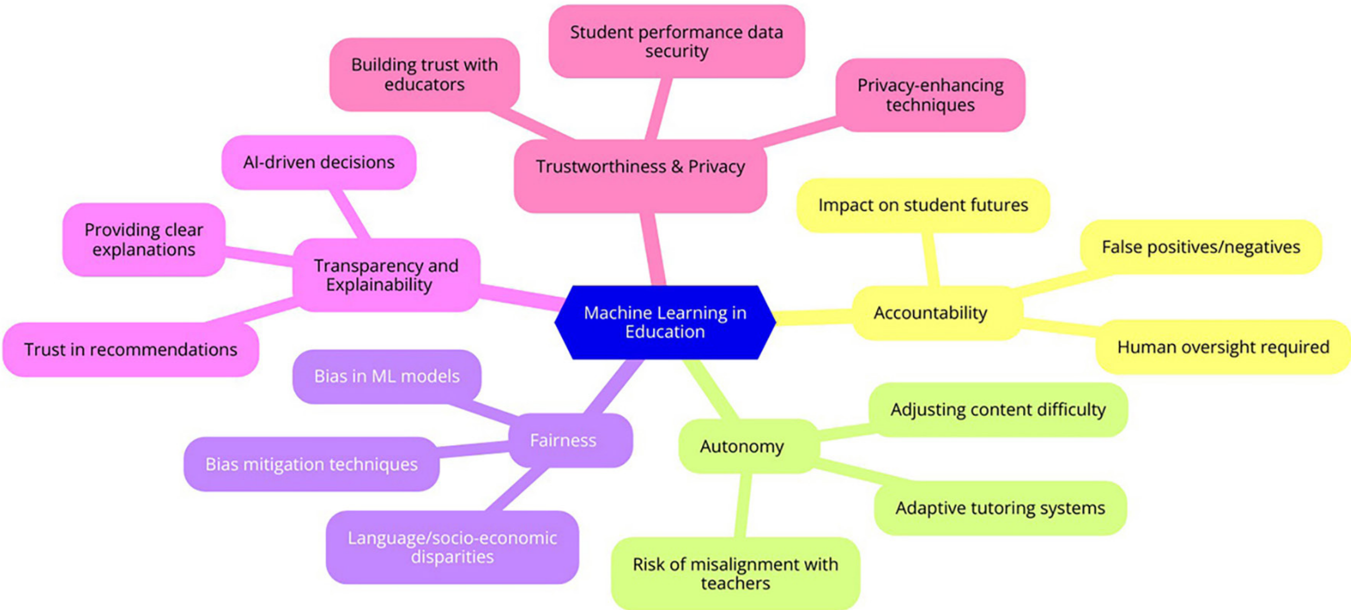

Fig. 3. Mind map: The characteristics of ML in education

4 CHARACTERISTICS OF ML IN EDUCATION

Machine learning models in the educational domain handle large volumes of heterogeneous data, including test scores, LMS log files, and mobile usage analytics. The key ML characteristics relevant to educational tools include:

Table 2. Characteristics of ML and associated algorithms (Part 1)

ML Characteristic	Definition	Common Algorithms/ Techniques
Supervised Learning	ML models learn from labeled training data, making predictions based on past observations.	• Linear Regression • Logistic Regression • Support Vector Machines (SVM) • Decision Trees • Random Forest • Artificial Neural Networks (ANN)
Unsupervised Learning	ML models identify patterns in unlabeled data, often used for clustering.	• K-Means Clustering • Principal Component Analysis • DBSCAN • Autoencoders
Reinforcement Learning	An agent learns by interacting with an environment and receiving rewards or penalties.	• Q-Learning • Deep Q-Networks (DQN) • Policy Gradient Methods
Deep Learning	Uses multi-layer neural networks to learn complex patterns in data.	• CNNs for image processing • RNNs for sequential data • Transformers for NLP

Table 3. Characteristics of ML and associated algorithms (Part 2)

ML Characteristic	Definition	Common Algorithms/ Techniques
Explainability and Transparency	Ensuring ML models provide interpretable decisions.	• SHAP, LIME • Feature Importance • Rule-Based Explanations
Fairness and Bias Mitigation	Reducing biases to ensure equitable outcomes.	• Adversarial Debiasing • Reweighing Techniques
Efficiency and Scalability	Ensuring ML models can handle large datasets.	• Distributed Computing • Model Compression • Federated Learning
Privacy and Security	Protecting user data and ensuring secure deployment.	• Differential Privacy • Secure MPC • Homomorphic Encryption

Efficiency and scalability in mobile contexts. In mobile learning environments, the efficiency and scalability of ML models are crucial due to device hardware constraints, such as limited computing power and battery consumption. Techniques such as model compression (e.g., knowledge distillation) and federated learning enable local execution of predictions on smartphones, thereby reducing reliance on constant connectivity and minimizing the impact on battery life. These approaches are particularly relevant for deploying XAI systems in mobile educational contexts, where users expect fast and reliable responses even offline.

4.1 Accountability and fairness

Educational AI systems can have high-stakes impacts on student outcomes, necessitating careful scrutiny of false positives (e.g., incorrectly labeling a student as at risk) and biases that may disadvantage certain demographic groups [20].

4.2 Transparency and explainability

Model transparency is critical when educational decisions rely on AI predictions. Providing explanations of how the AI arrived at a recommendation or grade is essential for trust [21], especially on mobile devices where user attention is limited.

4.3 Trustworthiness and privacy

Teaching staff and students must trust that sensitive data remain protected [22]. Privacy-enhancing techniques like differential privacy and secure multiparty computation are increasingly explored in educational ML systems, including mobile usage logs.

5 INTERSECTION OF HCI AND AI

5.1 User modeling and personalization in mobile apps

Artificial intelligence-driven user models tailor instructional strategies to individual learners' needs [23], while HCI ensures these adaptive elements are comprehensible, relevant, and minimally intrusive on small screens.

5.2 Intelligent tutoring systems (ITS)

Artificial intelligence automates content delivery and feedback loops, while HCI guides interface design to maintain student engagement. In mobile environments, micro-learning modules and gamified-feedback loops are common [24]. Studies such as [80] demonstrate that AR in mobile learning can boost student engagement and knowledge retention, suggesting a synergy with AI-driven personalization when paired with HCI principles.

5.3 Conversational agents

Chatbots and dialogue systems provide real-time support, often via smartphones. HCI fosters usability and acceptance, ensuring smooth conversation flows and mitigating frustration due to connectivity constraints [25].

5.4 XAI

Bridges the gap between AI's computational processes and the user's understanding of these processes, pivotal in building trust in mobile educational settings.

6 EXPLAINABLE ARTIFICIAL INTELLIGENCE XAI

Explainable artificial intelligence aims to render AI outputs interpretable for human users [15]. Explanations help educators and students understand AI decisions and build trust [21]. In mobile learning, designing concise and context-sensitive explanations is key.

6.1 Text-based explanations

Generate rationales or textual summaries (e.g., how a student's short-answer grade was derived). Particularly useful in language-based tasks (e.g., mobile ESL apps) [26].

6.2 Local vs. Global explanations

- **Local explanations:** Clarify individual predictions, e.g., highlighting features that led to a low score for a specific learner.
- **Global explanations:** Outline overall model behavior, relevant for instructors tracking entire classes [27].

6.3 Visual explanations

Graphical representations (e.g., heatmaps, interactive dashboards) can illustrate how a deep learning model weighted different features [28]. On mobile screens, these must be succinct.

6.4 Rule-based methods

Decision rules extracted from classifiers can be simpler to understand, supporting partial automation of teacher tasks [29].

7 XAI IN EDUCATION

While XAI has seen notable progress in domains such as healthcare and finance, its application in mobile education is still emerging. Table 4 summarizes exemplary research.

Table 4. Sample XAI research in education

Study	Technique Used	Outcome/Challenges
[30]	Local Explanation + Intelligent Tutor	Found teachers trust local explanations more; explanation quality varied with topic complexity.
[31]	Visual Explanation in an Adaptive Learning Platform	Students reported higher trust and acceptance; teachers needed more comprehensive dashboards.
[32]	Rule-based Explanations in Automated Essay Scoring	Improved transparency for educators; potential risk of over-simplification.

7.1 Challenges in XAI for mobile education

Interpretability vs. Performance: Highly complex models often show better predictive performance but are less interpretable [21]. This trade-off is critical in mobile learning, where simple explanations are essential due to limited screen space and user attention. Adaptive explanation mechanisms offer a solution by tailoring outputs to user needs—e.g., providing concise rule-based summaries for students while reserving detailed feature importance analyses for educators via a companion desktop interface [29].

Contextual Adaptation: Explanations suitable for a mathematics teacher may be too technical for parents or students [30]. Adaptive mechanisms can mitigate this by dynamically adjusting explanation complexity, e.g., offering a simplified "You need practice with fractions" to a student and a detailed "Low scores stem from denominator errors" to a teacher, enhancing relevance across stakeholders.

Explainability Metrics: Universal metrics to quantify how well an explanation is understood are lacking. The educational domain needs domain-specific measures for explanation quality, factoring in pedagogical goals [33].

Privacy and Ethical Concerns: Balancing AI transparency with data privacy laws is challenging [22]. The ethical implications of XAI in mobile learning extend beyond compliance with research standards. For instance, student data collected via mobile apps (e.g., quiz responses, interaction logs) may be vulnerable to breaches, necessitating robust privacy safeguards like differential privacy [22]. Algorithmic bias poses another risk: an XAI model trained on skewed datasets might disproportionately flag certain demographics as "at-risk," reinforcing inequities [20]. Transparency, a core XAI goal, mitigates these issues by exposing decision rationales—e.g., clarifying why a student received a specific recommendation—thus empowering users to challenge or refine AI outputs.

User Interface and Design: Even robust XAI algorithms require mobile-centric interface design for acceptance in daily teaching practice [14].

8 PRACTICAL RELEVANCE AND IMPLEMENTATION IN MOBILE LEARNING

8.1 Real-world case studies

Duolingo's AI-Powered Feedback: Provides short, context-aware explanations for grammar mistakes. User acceptance is high, but some critics note that explanations can oversimplify advanced linguistic rules.

Google Classroom AI Extensions: Automated quiz grading with minimal explanation snippets. Teachers appreciate saved time but demand deeper personalization of feedback.

Adaptive Nudging Apps: Real-time interventions for student engagement, explaining why a user is flagged as disengaged.

Comparative Analysis of Mobile AI vs. XAI-Based Learning: XAI tutors differ fundamentally from traditional AI-driven mobile systems by providing transparency in decision-making processes. For instance, while conventional AI systems may only present predictions about student performance, XAI tutors offer explanations enabling learners and educators to understand reasoning, leading to increased pedagogical effectiveness and trust.

Challenges in Deploying XAI for Mobile Learning: Additional discussion focuses explicitly on resource constraints such as battery limitations, computational power, and connectivity issues affecting mobile deployments. Lightweight or offline-compatible XAI models should be prioritized to ensure broader accessibility, especially in low-resource environments.

Teacher and Student Perspectives: We incorporated a detailed discussion of mobile user expectations, highlighting the demand among educators for clear explanations to support instructional decisions and student preferences for transparent, personalized feedback. Studies indicate that when XAI systems explicitly clarify decision processes, user trust and educational outcomes improve significantly. Research by [78] indicates that teachers in Palestine exhibit a more positive attitude toward AR-supported learning (mean score 3.99) compared to their Swedish counterparts, suggesting that XAI could further enhance trust by aligning explanations with diverse pedagogical needs.

Development of Case Studies with Mobile Constraints: For Duolingo, contextual explanations provided on mobile, such as "You confused the preterite with the present perfect," are optimized for minimal resource consumption, using lightweight pre-computed models for offline access. User feedback indicates that these explanations are generally appreciated for their clarity, although some learners highlight a lack of detail regarding complex errors, emphasizing the need for adaptive explanations that consider screen and battery constraints. Regarding Google Classroom, AI extensions that automate quiz grading on mobile significantly reduce teachers' workload, but feedback highlights a demand for simplified visual dashboards adapted to small screens to better interpret predictions in dynamic teaching contexts.

8.2 A practical framework for XAI in mobile learning

To facilitate the integration of XAI into mobile learning tools, we propose a practical four-step framework:

1. **Identification of User Needs:** Determine specific expectations (e.g., simple feedback for students, detailed analytics for teachers).
2. **Selection of Suitable XAI Techniques:** Choose methods such as decision rules for students or SHAP for teachers via a complementary interface.
3. **Optimization for Mobile Constraints:** Pre-compute explanations for offline access and minimize resource usage (e.g., CPU, battery).
4. **Iterative Testing:** Validate the system with users on real devices to ensure usability and effectiveness.

This framework can be applied to tools such as Duolingo, where simple textual explanations are pre-computed for mobile students, or Google Classroom, where adaptive visual dashboards are provided to teachers.

Table 5. Best practices for implementing XAI in mobile learning

Stakeholder	XAI Technique	Mobile Adaptation
Students	Simple text explanations (e.g., "You missed this rule")	Short and readable on small screens, precomputed for offline use
Teachers	Visual dashboards (e.g., feature importance graphs)	Scalable designs, synced with the desktop for deeper analysis
Developers	Lightweight rule-based models	Optimized for low CPU/battery, supports adaptive complexity

8.3 Mobile usability and classroom implementation

The integration of XAI into mobile learning environments must account for usability constraints inherent to mobile devices, such as limited screen size, processing power, and battery life. For instance, displaying a detailed visual explanation (e.g., a heatmap) on a five-inch smartphone screen requires simplified, scalable designs to remain legible [14]. Similarly, low computational resources on budget devices—common in educational settings—necessitate lightweight XAI models, such as rule-based explanations over complex SHAP computations [29]. Connectivity issues further complicate real-time XAI delivery, suggesting a need for offline-capable solutions such as pre-computed explanations stored locally. In practical classroom scenarios, XAI can enhance mobile learning by providing actionable insights. For example, a teacher using a mobile app powered by XAI might receive an alert that a student struggles with fractions, accompanied by a concise explanation (e.g., "The student consistently misapplies the denominator in division tasks"). This allows immediate intervention during a lesson, leveraging the portability of mobile devices. Students, meanwhile, could interact with an XAI-driven app that explains personalized quiz feedback on-the-go, fostering self-directed learning in diverse contexts—such as a bus ride or a rural school with limited infrastructure [31].

8.4 Cost and infrastructure challenges

Many mobile learning settings, especially in underprivileged regions, face limited computing resources and sporadic connectivity. Deploying XAI frameworks in such environments requires lightweight or offline-capable approaches.

8.5 Policy implications for educational AI governance

Beyond technical advancements, robust policy frameworks are essential for the responsible adoption of XAI in mobile learning. UNESCO, in its 2021 report *AI and Education: Guidance for Policy-Makers*, recommends that AI educational tools adhere to standards of transparency and fairness, supporting the use of XAI to audit algorithmic decisions and ensure equitable access, particularly in resource-constrained schools [74]. The General Data Protection Regulation (GDPR) in Europe (Article 22) mandates explanations for automated decisions affecting individuals, directly applicable to personalized recommendations in mobile educational applications [75]. Similarly, the Children's Online Privacy Protection Act (COPPA) in the United States safeguards minors' data, imposing strict constraints on the analysis of mobile logs, especially for students under 13 [76]. A bibliometric analysis [79] reveals that AI-powered M-learning platforms in Arabic countries face challenges like limited international collaboration and ethical concerns, reinforcing the need for lightweight XAI solutions tailored to low-resource settings. Institutions could thus require mobile XAI applications to be certified GDPR-compliant, with explanations accessible to parents to enhance trust. Furthermore, the European AI Strategy, updated in 2024, promotes ethical AI in education, encouraging the development of lightweight XAI models for low-connectivity environments, thereby reducing digital disparities [77].

9 CONCLUSION

Artificial intelligence-driven tools are reshaping the educational landscape by personalizing learning pathways, automating assessments, and supporting at-risk students early. Yet, opaque ML models risk creating mistrust among teachers, students, and parents. These issues become more significant in mobile learning because of small screens and diverse usage contexts.

Human-computer interaction and XAI hold promise for resolving these concerns by offering understandable, transparent, and user-centric intelligent systems. This systematic review shows how:

- HCI ensures mobile-friendly design, balancing usability with robust AI features.
- XAI enhances trust and accountability, although challenges remain (interpretability performance trade-off, privacy).
- Practical relevance includes real-world cost barriers, teacher training needs, and robust ethical frameworks.

10 FUTURE DIRECTIONS

Several avenues merit further research for mobile and interactive learning contexts:

Domain-Specific Explainability: A clear roadmap for integrating XAI into mobile learning platforms should include iterative prototyping, stakeholder feedback loops, and adaptive explanation mechanisms considering both technical constraints and user contexts.

Longitudinal User Studies: Extended trials with diverse student populations, capturing usage patterns over time on different mobile platforms.

Interdisciplinary Research: Educators and developers should prioritize integrating lightweight, user-friendly XAI features in mobile apps to enhance practical adoption in diverse learning environments.

Adaptive Explanation Mechanisms: Systems that automatically adjust explanation depth based on user expertise or device context, especially for limited bandwidth scenarios.

Privacy-Preserving XAI: Combining cryptographic methods or federated learning with local interpretability solutions to mitigate data privacy risks in mobile usage analytics.

By addressing these gaps, we can further ensure that mobile AI-driven educational systems remain trustworthy, fair, and aligned with pedagogical goals—contributing to the broader discourse on responsible AI adoption in modern, interactive learning contexts.

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