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PAPER

Mobile-Based Intelligent Tutoring Systems: Enhancing Personalized Learning in Digital Education

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ABSTRACT

The proliferation of mobile technologies in educational contexts has catalysed the development of intelligent tutoring systems (ITS) that leverage artificial intelligence (AI) to deliver personalized, adaptive learning experiences. This paper presents a comprehensive review and conceptual framework examining the integration of mobile-based intelligent tutoring systems (M-ITS) in digital education environments. Drawing on self-determination theory (SDT), the technology acceptance model (TAM), and constructivist learning principles, this study investigates how M-ITS architectures comprising student modelling, domain modelling, pedagogical modules, and adaptive interfaces can enhance learner engagement, knowledge acquisition, and academic performance. Through a systematic analysis of recent empirical studies, theoretical frameworks, and technological implementations, the paper identifies critical design principles for effective M-ITS deployment, including personalization algorithms, gamified learning components, natural language processing capabilities, and real-time feedback mechanisms. Evidence suggests that M-ITS significantly improves learning outcomes across diverse learner populations, including neurodivergent students, English as a Foreign Language (EFL) learners, and higher education cohorts. Furthermore, the role of generative artificial intelligence (GenAI) as an emerging component in M-ITS is examined, highlighting its potential for dynamic content generation and conversational tutoring. The study concludes by proposing a research agenda addressing scalability, data privacy, pedagogical alignment, and cross-cultural adaptability of mobile intelligent tutoring solutions. These findings carry substantial implications for educators, instructional designers, policymakers, and technology developers working at the intersection of mobile learning and AI-driven pedagogy.

KEYWORDS

mobile learning (m-learning), intelligent tutoring systems (ITS), personalized learning, artificial intelligence (AI) in Education, quality education, gamification, generative AI (GenAI)

1 INTRODUCTION

The global expansion of mobile device adoption has fundamentally reshaped how learners interact with educational content. By 2024, there were over

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6.9 billion smartphone users worldwide, with mobile devices accounting for more than 58% of global internet traffic [36]. This unprecedented penetration has created a fertile ground for mobile learning (m-learning) platforms that transcend the spatial and temporal constraints of conventional classroom instruction. Within this rapidly evolving landscape, intelligent tutoring systems (ITS), computational platforms capable of emulating one-on-one human tutoring through adaptive instructional strategies, have emerged as one of the most consequential applications of artificial intelligence (AI) in education [1, 23].

Intelligent tutoring systems date to the pioneering work of Carbonell (1970) and were further developed through foundational frameworks such as SCHOLAR, LISP Tutor, and Cognitive Tutor [2, 9]. Contemporary ITS leverages machine learning, natural language processing (NLP), and big data analytics to model learner knowledge states, diagnose misconceptions, and dynamically scaffold learning experiences [41, 29]. The convergence of these capabilities with mobile computing infrastructure has given rise to mobile-based intelligent tutoring systems (M-ITS), which offer ubiquitous, context-aware, and highly personalized instruction at scale.

The importance of personalization in education has been well established. Research consistently demonstrates that learners benefit from instruction tailored to their cognitive profiles, prior knowledge, learning styles, and motivational orientations [30, 5]. M-ITS embodies this principle by continuously updating student models based on interaction data and adjusting content delivery accordingly. Moreover, the integration of gamification, social learning features, and multimodal content within M-ITS platforms has been shown to enhance learner engagement and emotional regulation, particularly among populations with diverse learning needs [19]. The adoption of AI-powered tools in higher education has also been shaped by motivational and behavioral frameworks, including self-determination theory (SDT) and the technology acceptance model (TAM), which illuminate the conditions under which learners voluntarily and effectively engage with digital tutoring tools [25].

Despite the growing body of research on ITS and m-learning individually, there remains a critical need for integrated conceptual frameworks that address the unique affordances and challenges of M-ITS deployments. This paper addresses this gap by: (1) reviewing the theoretical underpinnings of M-ITS design and adoption; (2) synthesizing empirical evidence on M-ITS efficacy across diverse educational contexts; (3) presenting a multi-component conceptual framework for M-ITS architecture; and (4) proposing directions for future research and practice. In doing so, this paper contributes to the growing discourse on intelligent, mobile-first educational technologies that are responsive to the needs of twenty-first-century learners.

2 LITERATURE REVIEW

2.1 Foundations of intelligent tutoring systems

Intelligent tutoring systems represent a class of computer-based educational systems that provide individualized instruction without requiring direct human teacher intervention [44]. The canonical ITS architecture, as articulated by [28] and elaborated by [34], comprises four core modules: (1) the domain model, which encodes expert knowledge of the subject matter; (2) the student model, which represents the learner's current state of knowledge, errors, and misconceptions; (3) the pedagogical model, which governs instructional decision-making; and (4) the user interface, through which the learner interacts with the system. Subsequent advances have extended this architecture to include metacognitive components, affective modeling, and collaborative learning modules [18, 16].

Meta-analytic evidence consistently attests to the instructional effectiveness of ITS. [23] conducted a landmark meta-analysis of 50 controlled studies and reported effect sizes ranging from 0.66 to 1.04 standard deviations in favor of ITS over conventional instruction, an effect broadly consistent with [5]'s tutoring benchmark of two standard deviations. More recent analyses have confirmed these findings across STEM subjects, language learning, and professional training contexts [29, 27].

2.2 Mobile learning and educational technology

Mobile learning encompasses any educational activity mediated by a portable, internet-connected device, including smartphones, tablets, and wearables [39, 10]. The defining affordances of m-learning ubiquity, connectivity, portability, and context-sensitivity make it uniquely suited to support just-in-time learning, microlearning, and spaced practice, all of which are evidence-based strategies for durable knowledge retention [22, 37]. Empirical reviews of m-learning, interventions have generally reported positive effects on learner performance and engagement, though effect magnitudes are moderated by pedagogical design quality, learner characteristics, and technological infrastructure [37, 11].

Mobile learning adoption in higher education has accelerated considerably in the post-pandemic era, driven by institutional mandates for flexible delivery and the widespread availability of mobile broadband. Within this context, the integration of generative AI (GenAI) capabilities into mobile educational tools has emerged as a particularly consequential development. [25] Examined GenAI adoption in EFL higher education settings using a dual-model approach integrating SDT and TAM, finding that perceived autonomy support, competence, and perceived usefulness were significant predictors of learners' behavioural intentions to use GenAI-powered tools. These findings underscore the importance of motivational design in M-ITS development.

2.3 Personalization and adaptive learning technologies

Personalized learning instruction responsive to individual learner needs, interests, and pace has long been a central aspiration of educational technology [30]. Adaptive learning systems operationalize this aspiration through algorithms that dynamically adjust content difficulty, sequencing, and modality based on ongoing assessment of learner performance [40]. Machine learning approaches, including Bayesian knowledge tracing, deep knowledge tracing (DKT), and reinforcement learning, have substantially advanced the sophistication of student modeling within ITS platforms [9, 33, 7]. More recently, [45] demonstrated that integrating heterogeneous network graphs with personalized preference modeling within a mobile learning framework enables adaptive learning path recommendations that effectively transition learners from traditional classroom constraints toward flexible, individualized digital environments, underscoring the growing role of intelligent mobile architectures in operationalizing adaptive pedagogy.

The application of personalization technologies to diverse learner populations has attracted increasing scholarly attention. [19] Investigated the impact of gamified learning environments on neurodivergent English learners in digital classrooms, demonstrating significant improvements in learner engagement and emotional regulation relative to non-gamified control conditions. These findings have important implications for the inclusive design of M-ITS, suggesting that adaptive gamification mechanisms can serve as effective personalization tools for learners whose motivational and affective profiles differ from neurotypical norms.

2.4 Theoretical frameworks underpinning M-ITS design

Several theoretical frameworks inform the design and evaluation of M-ITS [43]. The zone of proximal development (ZPD) provides the foundational rationale for adaptive scaffolding, the idea that instruction is most effective when it operates at the frontier of the learner's current competence. Cognitive load theory [38] informs interface design principles aimed at minimizing extraneous cognitive demands while maximizing germane learning. Constructivist learning theory [31, 20] emphasizes the importance of active, reflective, and contextualized knowledge construction, which M-ITS can support through problem-solving environments and simulations.

Self-determination theory [13, 14] offers a motivational lens, positing that sustained engagement with learning tools depends on the degree to which they satisfy basic psychological needs for autonomy, competence, and relatedness. M-ITS designs that incorporate learner agency, mastery-oriented feedback, and social learning features are theoretically positioned to satisfy these needs and thus foster intrinsic motivation. The Technology Acceptance Model [12] and its extensions provide complementary insights into the attitudinal antecedents of M-ITS adoption, identifying perceived ease of use and perceived usefulness as key determinants of behavioral intention [32, 25].

3 A CONCEPTUAL FRAMEWORK FOR MOBILE-BASED INTELLIGENT TUTORING SYSTEMS

3.1 Framework overview

Building on the theoretical and empirical foundations reviewed above, this paper proposes an integrated conceptual framework for M-ITS design and deployment. The framework, termed the Mobile Adaptive Personalized Tutoring (MAPT) framework, comprises five interacting layers: (1) the Learner Profile Layer, (2) the Knowledge Representation Layer, (3) the Pedagogical Intelligence Layer, (4) the Mobile Interface Layer, and (5) the Evaluation and Analytics Layer. Each layer contributes to a coherent, learner-centred system that adapts to the unique needs, context, and trajectory of individual learners.

3.2 Learner profile layer

The learner profile layer constitutes the epistemological heart of the M-ITS, continuously constructing and updating a multi-dimensional model of the learner. This model encompasses cognitive dimensions, prior knowledge, misconceptions, learning pace, and skill mastery as well as affective dimensions, including emotional state, engagement level, and motivational orientation. Drawing on insights from affective computing [32] and knowledge tracing models [9, 33], the Learner Profile Layer integrates data streams from interaction logs, performance metrics, physiological signals (where available via mobile sensors), and self-report instruments. Dynamic

Bayesian networks and deep learning models are employed to infer latent knowledge states and predict learning trajectories.

3.3 Knowledge representation layer

The Knowledge Representation Layer encodes the subject matter to be taught in a structured, machine-interpretable format. Contemporary M-ITS implementations employ ontology-based knowledge graphs, concept dependency networks, and hierarchical skill trees to represent domain knowledge with sufficient granularity for fine-grained adaptive sequencing [18, 24]. The integration of large language models (LLMs) and generative AI within this layer enables dynamic content generation, the synthesis of personalized explanations, and conversational tutoring interactions that approximate the richness of human expert dialogue [21].

3.4 Pedagogical intelligence layer

The Pedagogical Intelligence Layer governs instructional decision-making, selecting learning activities, feedback strategies, and difficulty levels that are optimally matched to the current learner state. Reinforcement learning algorithms have demonstrated promise for optimizing pedagogical sequences in ITS environments [7, 8]. The MAPT framework advocates for a multi-strategy pedagogical engine that can dynamically switch between Socratic dialogue, example-based instruction, problem-solving practice, and metacognitive prompting based on real-time assessment of learner performance and affective state. Gamification elements, points, badges, leaderboards, narrative quests, and adaptive challenges are integrated at this layer to leverage motivational affordances identified in the empirical literature [19, 15].

3.5 Mobile interface layer

The Mobile Interface Layer addresses the unique interaction constraints and affordances of mobile devices. Effective M-ITS interfaces must balance information richness with the limited screen real estate and input modalities of smartphones and tablets. Design principles derived from cognitive load theory [38] and Universal Design for Learning (UDL) [6] inform the construction of accessible, multimodal interfaces that accommodate diverse learner needs, including those of neuro-divergent populations [19]. Gesture-based navigation, voice interaction, augmented reality (AR) overlays, and push notification systems are among the interface modalities that contemporary M-ITS can leverage to deliver seamless, context-aware learning experiences.

3.6 Evaluation and analytics layer

The evaluation and analytics layer provide the feedback loop through which M-ITS systems are continuously improved. Learning analytics dashboards present learner progress data to both students and instructors, supporting metacognitive reflection and formative assessment [35, 17]. Institutional-level analytics aggregate individual learning data to identify systemic patterns, enabling evidence-based curriculum design and policy decisions. Ethical data governance protocols, including privacy-by-design principles and differential privacy techniques, are essential components of this layer, given the sensitivity of educational data collected through mobile devices.

3.7 Empirical evidence on M-Its efficacy

Learning outcomes. A growing body of controlled experimental and quasi-experimental studies attests to the efficacy of M-ITS in improving academic performance. [37] Conducted a meta-analysis of 59 studies on mobile learning and found a moderate positive effect on learning achievement (d = 0.523). Studies specifically examining AI-driven adaptive components within mobile platforms have reported even larger effect sizes, with some investigations documenting effect magnitudes approaching those reported by [23] for desktop-based ITS. In mathematics education, mobile adaptive systems employing DKT-based student modeling have been shown to significantly outperform non-adaptive digital curricula in promoting procedural fluency and conceptual understanding [33, 30]. Complementing these findings, [3] evaluated an AI-driven personalized mobile learning platform at Mohammed VI Polytechnic University, reporting significant improvements in academic achievement and educational progress, with learners benefiting from AI-powered mentoring seamlessly integrated into their mobile course interfaces—offering direct empirical support for the pedagogical viability of the M-ITS model advanced in this paper.

Engagement and motivation. Sustained learner engagement represents a critical mediator between ITS use and learning outcomes. Research has consistently demonstrated that well-designed M-ITS platforms, particularly those incorporating gamification and social learning features, elicit higher levels of time-on-task, intrinsic motivation, and self-regulated learning behavior compared to passive digital content delivery [15]. The relevance of these findings extends to diverse learner populations. [19] Provided compelling evidence that gamified digital learning environments significantly enhanced both engagement and emotional regulation among neurodivergent English learners, a population for whom conventional instructional formats often present motivational and regulatory challenges. These findings suggest that the adaptive, multimodal, and gamified features of M-ITS hold particular promise for inclusive education.

GenAI integration in mobile educational tools. The emergence of large language models and generative AI has opened new frontiers for M-ITS design. GenAI-powered conversational tutors can engage learners in open-ended dialogue, provide on-demand explanations in natural language, generate personalized practice problems, and offer formative feedback at a level of granularity and responsiveness previously achievable only through human tutoring [21, 26]. [25] Investigated the determinants of GenAI adoption among EFL higher education learners, employing an integrated SDT-TAM model. Their findings revealed that intrinsic motivation, operationalized through SDT's autonomy, competence, and relatedness constructs, operated alongside TAM's perceived usefulness and ease-of-use perceptions to predict adoption intentions. These results underscore the necessity of designing GenAI-integrated M-ITS that are not only functionally effective but also motivationally supportive.

Inclusive design and diverse learner populations. A defining aspiration of M-ITS development is universal accessibility, the capacity to serve learners across the full spectrum of cognitive, linguistic, cultural, and developmental diversity. UDL principles advocate for multiple means of representation, action and expression, and engagement as the basis for inclusive instructional design [6]. M-ITS platforms that implement these principles through adaptive content presentation, multimodal feedback, and culturally responsive content selection are better positioned to serve learners from diverse backgrounds. Research on EFL learners in technology-enhanced environments has highlighted the importance of motivational scaffolding and autonomous learning support in AI-mediated instruction [25, 19], reinforcing the design imperative for motivationally intelligent M-ITS.

4 CHALLENGES AND LIMITATIONS

4.1 Technical challenges

The deployment of M-ITS at scale confronts a range of technical challenges. First, the computational demands of sophisticated student modelling and generative AI components may strain the processing and battery resources of low-end mobile devices, creating equity concerns in resource-constrained educational contexts. Second, the reliance on persistent internet connectivity for real-time adaptive processing is problematic in regions with limited broadband infrastructure. Edge computing approaches, which offload processing to on-device models, represent a promising mitigation strategy but introduce trade-offs in model sophistication. Third, the heterogeneity of mobile operating systems, screen sizes, and input modalities complicates the development of universally consistent user experience across device ecosystems.

4.2 Pedagogical challenges

From a pedagogical standpoint, the effectiveness of M-ITS is contingent on the fidelity with which domain knowledge is encoded and the validity of the student models employed. Incomplete or inaccurate knowledge representations can lead to suboptimal instructional sequences that fail to address genuine learner needs. The 'cold start problem,' the challenge of accurately modeling learners with limited interaction history, remains a significant obstacle in early-stage ITS deployment [40]. Moreover, the emphasis on quantifiable performance metrics in most M-ITS platforms may inadvertently neglect higher-order learning competencies such as critical thinking, creativity, and collaborative problem-solving.

4.3 Ethical and privacy concerns

The collection and processing of sensitive learner data through mobile platforms raises profound ethical and privacy concerns. M-ITS systems that continuously monitor learner behaviour, including physiological signals, attention patterns, and affective states, must navigate complex regulatory frameworks, including GDPR in Europe and FERPA in the United States. The potential for algorithmic bias wherein student models systematically disadvantage learners from underrepresented demographic groups demands rigorous fairness auditing of M-ITS algorithms [4]. Transparent data governance frameworks and participatory design approaches involving learners, educators, and community stakeholders are essential for ensuring the ethical deployment of M-ITS.

5 DISCUSSION

The evidence reviewed in this paper supports a cautiously optimistic assessment of the potential of M-ITS to transform personalized learning in digital education. The convergence of advanced AI techniques, machine learning, NLP, and generative AI with the ubiquity and context-sensitivity of mobile platforms creates an unprecedented opportunity to deliver individualized, high-quality instruction to learners regardless of geography, socioeconomic status, or institutional affiliation. The MAPT framework proposed herein provides a theoretically grounded architecture for realizing this potential, integrating insights from cognitive science, motivational psychology, and learning analytics.

Particularly noteworthy are the implications for inclusive education. The findings of [19] regarding gamified learning for neurodivergent English learners demonstrate that M-ITS designed with adaptive gamification and affective support can meaningfully improve outcomes for populations that have historically been underserved by one-size-fits-all instructional approaches. Similarly, the SDT-TAM framework applied by [25] to GenAI adoption in EFL higher education offers a nuanced account of how intrinsic motivation and perceived utility jointly shape learner engagement with AI-powered tools, insights directly applicable to the motivational architecture of M-ITS. Together, these studies suggest that successful M-ITS deployment requires attending not only to the technical sophistication of the underlying AI but also to the motivational, affective, and social dimensions of the learning experience.

The integration of generative AI represents a particularly significant frontier. LLM-powered conversational tutors embedded in mobile applications can provide naturalistic, responsive, and contextually sensitive instructional dialogue at a scale and cost that human tutors cannot match. However, the responsible deployment of GenAI in M-ITS demands careful attention to issues of accuracy, transparency, and pedagogical alignment. AI-generated explanations and feedback must be validated against expert pedagogical standards, and mechanisms for learner and instructor oversight must be incorporated into system design.

From a theoretical standpoint, the MAPT framework contributes to the literature by providing an integrative architecture that bridges the gap between ITS design principles and mobile learning affordances. The explicit incorporation of motivational and affective modelling components informed by SDT and affective computing research represents a significant advance over earlier ITS frameworks that focused predominantly on cognitive dimensions. Future empirical work should evaluate the predictive validity of each MAPT layer and the interaction effects between framework components in naturalistic M-ITS deployments.

5.1 Implications for practice and policy

For educators and instructional designers. Educators and instructional designers should approach M-ITS as pedagogical tools that require thoughtful integration into broader instructional ecosystems rather than standalone replacements for human teaching. Effective M-ITS implementation involves careful alignment between system capabilities and course learning objectives, ongoing monitoring of learner interaction data, and iterative refinement of M-ITS configurations based on formative evidence. Professional development programs that equip educators with competencies in AI literacy, learning analytics interpretation, and inclusive digital pedagogy are essential prerequisites for successful M-ITS adoption.

For technology developers. Developers of M-ITS platforms should prioritize user-centred design processes that involve learners, educators, and accessibility specialists from the earliest stages of development. Adherence to UDL principles, open educational standards, and interoperability specifications will facilitate wider adoption and integration. Investment in explainable AI techniques will enhance trust and transparency in adaptive decision-making. The incorporation of differential privacy and federated learning approaches can help reconcile the tension between personalization efficacy and data privacy.

For policymakers. Educational policymakers should develop regulatory frameworks that establish clear standards for M-ITS data governance, algorithmic fairness, and pedagogical quality assurance. Public investment in digital infrastructure, particularly broadband connectivity in underserved communities, is a prerequisite for equitable M-ITS access. International collaboration on open educational resource repositories and shared student model standards could accelerate the development of high-quality M-ITS solutions for underrepresented languages and curricula.

5.2 Future research directions

Several priority directions emerge from this review for advancing the M-ITS research agenda. First, longitudinal studies examining the sustained effects of M-ITS use on learning outcomes, self-regulated learning, and academic motivation are needed to complement the predominantly short-term experimental evidence currently available. Second, cross-cultural studies exploring how M-ITS effectiveness varies across different national, linguistic, and sociocultural contexts will be essential for developing globally applicable design principles. Third, research on the optimal integration of human teachers with M-ITS, exploring collaborative intelligence models in which AI and human expertise are synergistically combined, represents a theoretically rich and practically significant frontier. Fourth, neuroimaging and psychophysiological studies examining the cognitive and affective mechanisms through which M-ITS effects are achieved would deepen the theoretical foundations of the field. Fifth, the ethical dimensions of M-ITS, including algorithmic fairness, consent, and data sovereignty, warrant dedicated investigation by interdisciplinary teams combining expertise in computer science, education, law, and ethics.

6 CONCLUSION

Mobile-based intelligent tutoring systems represent a powerful confluence of AI-driven personalization and mobile learning affordances with the potential to democratize access to high-quality, individualized instruction. This paper has reviewed the theoretical foundations, architectural components, and empirical evidence pertaining to M-ITS and has proposed the MAPT framework as an integrative guide for M-ITS design and evaluation. Evidence from gamified mobile learning contexts [19] and GenAI adoption studies [25] converges on the conclusion that effective M-ITS must attend holistically to cognitive, motivational, and affective dimensions of the learning experience. As artificial intelligence technologies continue to evolve at an accelerating pace, the challenge for the research community is to ensure that M-ITS development is guided by rigorous empirical evidence, inclusive design principles, and a steadfast commitment to the educational and ethical well-being of all learners.

6.1 Conflict of interest

The authors declare no conflict of interest.

6.2 Author contributions

Shamim Akhter: Conceptualization, methodology design, theoretical framework development, supervision of the overall research direction, critical review and editing of all manuscript drafts, and final approval of the submitted version.

Tribhuwan Kumar: Literature review and synthesis, empirical evidence analysis, writing of the main manuscript sections (Sections 2–4), data curation, and substantive contribution to the MAPT framework elaboration.

Musart Shaheen: Investigation, discussion, and implications drafting (Section 5); reference compilation; formatting and manuscript preparation; and contribution to the challenges and future research directions sections.

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