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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 24 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i24.58959

PAPER

AI- and IoT-Driven Mobile Learning Environments: A Framework for Educational Transformation, Workforce Development, and Digital Inclusion

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ABSTRACT

The integration of artificial intelligence (AI) and the Internet of Things (IoT) into mobile learning has gained significant scholarly and industry attention for their potential to deliver adaptive, context-aware, and inclusive educational experiences. AI–IoT-enhanced mobile platforms combine intelligent data analytics, real-time feedback systems, and connected devices to create immersive, location-based, and personalized learning environments. This study examines the design, implementation, and impact of AI–IoT-driven mobile learning ecosystems in advancing educational transformation, workforce development, and digital inclusion. Drawing on socio-technical systems (STS) theory, the study employs a mixed-methods approach, integrating a systematic review of peer-reviewed literature (2018–2025) with multi-sector case studies across K–12, higher education, and industry-based training. The analysis investigates technological features, pedagogical strategies, and deployment frameworks, identifying key benefits such as enhanced learner engagement, improved skill acquisition, greater accessibility for underserved communities, and increased learning autonomy. It also addresses critical challenges, including algorithmic bias, data privacy concerns, unequal device access, and cultural or linguistic adaptability. Findings indicate that AI–IoT integration can optimize adaptive content delivery, support context-aware experiential learning, and enable evidence-based instructional design when guided by ethical and equity-focused principles.

KEYWORDS

mobile learning, artificial intelligence (AI)-driven education, Internet of Things (IoT)-enabled learning, educational technology, workforce development

1 INTRODUCTION

The convergence of artificial intelligence (AI) and the Internet of Things (IoT) in mobile learning (m-learning) has emerged as a transformative approach

Hijazi, S., Mokal, M. N., Halder, A., Victor, V., John, G. (2025). AI- and IoT-Driven Mobile Learning Environments: A Framework for Educational Transformation, Workforce Development, and Digital Inclusion. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(24), pp. 4–17. https://doi.org/10.3991/ijim.v19i24.58959

Article submitted 2025-07-30. Revision uploaded 2025-09-24. Final acceptance 2025-10-02.

to education, garnering significant scholarly and practical attention. Mobile learning has undergone a substantial evolution, shifting from an auxiliary instructional tool to a dynamic educational paradigm that redefines how knowledge is accessed, delivered, and applied across formal, non-formal, and lifelong learning contexts [1]. The proliferation of smartphones, pervasive wireless connectivity, and cloud computing infrastructures has enabled AI–IoT-enhanced mobile platforms to deliver adaptive, context-aware, and personalized learning experiences, transforming conventional static content delivery into dynamic socio-technical ecosystems capable of supporting diverse learner needs.

Artificial intelligence applications, including intelligent tutoring systems, predictive analytics, recommender algorithms, natural language processing, and generative content applications, provide personalized learning pathways, automated feedback, and predictive scaffolding, thereby enhancing learner engagement, cognitive development, and skill acquisition [2]. Concurrently, IoT technologies embed learning interactions into sensor-rich, data-driven environments, leveraging wearable devices, RFID-based tracking, environmental sensors, and smart devices to provide contextually relevant data that informs instructional strategies and enhances immersive learning experiences [3]. The convergence of AI and IoT, commonly referred to as AIoT, creates location-based, immersive, and experiential learning opportunities, facilitating real-time monitoring of learner progress, cognitive and affective states, and environmental variables [4].

Pedagogically, this synergy repositions mobile learning as a socio-technical ecosystem, adapting dynamically to learners' contexts, needs, and identities. AI–IoT-enabled environments foster experiential, authentic, and competency-based learning approaches, bridging the gap between theoretical knowledge and real-world application. Such systems align with the emerging global demand for lifelong, skill-oriented, and industry-responsive education models [5]. The development of AI–IoT ecosystems is motivated by three critical imperatives. First, the digital economy requires a workforce equipped with transversal skills, including creativity, adaptability, and advanced digital literacy [6]. AI–IoT mobile platforms provide scalable, job-relevant microlearning and upskilling to match the changing labor market requirements in real time.

Second, ongoing digital divides, arising from socio-economic inequality, geographical distance, and infrastructure inequity, highlight the importance of learning technologies that are inclusive and accessible. There is evidence to support wide-reaching mobile-first AI–IoT solutions offering equitable access to the underserved in view of infrastructural constraints and multiple modality delivery [7]. Third, there is a growing awareness of the need for equity-oriented educational change. Lack of sound policy may make AI–IoT applications grow existing inequalities through algorithmic bias, surveillance, use of non-local languages, and culturally insensitive designs [8].

Despite the promise, AI–IoT-based mobile learning encounters considerable challenges. Algorithmic bias, data privacy issues, inequitable access to devices, governance gaps, and inappropriateness for cultural or linguistic use may hinder use and further exacerbate current inequities [9]. However, the ability of IoT to contextualize learning experiences, particularly in low-resource or cross-cultural environments, has been under-investigated, and there is a critical research gap [10].

Objectives: This study aims to: Conceptualize AI–IoT convergence in mobile learning as a socio-technical ecosystem. Evaluate empirical evidence on design, implementation, and impact across K–12, higher education, and industry-based training. Offer actionable recommendations for scalable, equitable, and culturally responsive deployment of AI–IoT mobile learning systems. The study integrates AI and IoT into a unified socio-technical perspective, bridging global technological innovation with local educational contexts and addressing equity, ethics, and sustainability in digital learning. Methodologically, it is mixed-method, with a systematic review of academic literature (2018–2025) and cross-section analysis regarding technological characteristics, pedagogical approaches, and design frameworks. This approach introduces novelty through integrating AI and IoT into a cohesive socio-technical perspective that connects how global technological innovation can be reconciled with local educational realities and how ethical, equity, and sustainability issues in digital learning can be addressed [11].

Artificial intelligence and IoT integration in the mobile learning space requires a more subtle beam when technological advancements are merged with socio-pedagogical dynamism. Hence, the study is anchored on socio-technical systems (STS) Theory. Based on Organizational Theory in the mid-20th century, STS theory assumes that the effectiveness of technology is anchored in the fitness between technical infrastructures and social subsystems, which include cultural mores, institutional routines, and human activity [12].

In this context, digital transformation is not a technical fix but a co-evolution of technological design, pedagogic innovation, and social-cultural acclimatization. Under AI–IoT-enabled mobile learning, STS theory figurates technologies as socio-technical assemblages in which technologies are used and transformed by users, institutions, and culture, and users, institutions, and culture are being intervened and affected by technologies [13]. This model allows for a comprehensive analysis of MLEs in three interrelated dimensions: technological, pedagogical, and sociocultural.

2 LITERATURE REVIEW

The integration of AI and IoT in mobile learning settings represents a disruptive move from traditional pedagogies. This integration is now more commonly scrutinized through the prism of STS theory that considers the interplay between technology and humans in organizational contexts. AI as a socio-technical ecosystem: AI is part of the socio-technical ecosystem that shapes and is shaped by the problems that AI is designed to address [14]. As we have shown in this paper, this perspective is indispensable for building AI–IoT systems that are state-of-the-art and at the same time ethical and context-aware.

Recent studies have underscored the necessity to integrate AI and IoT into the personalization of learning experiences. For instance, [15] has done a meta-analysis of 76 articles and concluded that digital ecosystems, including AI and IoT, are getting more aligned with personalization of learning that leads to improvement in student engagement and learning. He has also found that the influence of AI adaptive systems on the enhancement of cooperative problem-solving skills was another influential reason driving context-aware learning systems.

However, while there is impressive technological advancement, the application of AIoT systems also needs to be mindful of the social-cultural context that it is being developed for. The efficiency of such systems is premised on a good understanding and fitting in of local educational systems, child stuff upbringings, parental roles, cultural expectations, and overall societal values [16]. This necessitates a widespread perspective on AI–IoT systems design and deployment that they should be efficient in the context, but not at the cost of fairness and cultural sensitivity.

AI–IoT technologies have witnessed both excitement and concern in K–12 schools. Second, a follow-up study, conducted [17], focused on K–12 AI education practice in the classroom between 2018 and 2023, finding trends in teaching methods and students' learning achievement. While the research concluded that AI tools have the potential to benefit personalized learning, we remain concerned about data privacy and equity. In a noteworthy report, nearly 70% of the parents did not support sharing student data with AI systems and claimed that data privacy and equitable use were barriers [18].

Because of these concerns, transparent data mechanisms and strong privacy assurances in AI–IoT systems are necessary. Failing to confront these unresolved issues could mean that the promise of personalized learning is outweighed by ethical and legal concerns. Hence, it is necessary to set clear rules and standards regulating how data is collected, used, and shared to protect students' rights.

Artificial intelligence–IoT integration in higher education has been linked to teaching and learning enhancements. Furthermore, [19] looked at using an AI-powered Mobile Learning system to imbibe innovation and reform in education and particularly higher education. apps developed with AI on soft computing networks can improve critical thinking skills of the students, making them more interested in the academic subjects, says the report. Furthermore, [20] investigated the impact of AI–learning management system (LMS) integration on educational quality, student satisfaction, and institutional resiliency and found that personalization and decision support could be highly potential with data-driven learning.

These advancements suggest that AI–IoT systems could be of great value to the potential transformation of higher education by the means of hyper personalization of learning environments and informed decisions. However, the successful operationalization of these systems requires the following: infrastructure for operations, training of human resources for operations for operations, and institutional support for bridging the gaps and employing them to the fullest.

This shift reflects a need for a holistic mechanism for the coordination of educational outputs to meet industry requirements. Through partnerships with education and industry, AI–IoT Systems can be used to organize course content, which is much more responsive to the job market and drives employability and competitiveness.

There are profound implications for equity, ethics, and sustainability associated with the escalation of AI–IoT mobile learning platforms. Research on multilingual and digital learning has highlighted that while technology holds promise for inclusive education, disparities in access and use persist, especially in marginalized and underserved communities, raising critical questions of digital equity [21]. Studies on remote education for learners with special needs similarly stress that inclusive design is essential to ensure fair participation and engagement for all learners, regardless of background [22].

Ethical considerations are also central: IoT-integrated digital education research indicates not only significant improvements in students' digital literacy but also heightened awareness of ethical issues related to data, programming, and responsible use of emerging technologies [23].

Finally, sustainability must be addressed; while AI and IoT applications can support scalable, personalized learning aligned with the United Nations Sustainable Development Goal 4, concerns remain regarding long-term sustainability, including equitable infrastructure, ethical design, and the environmental footprint of digital deployments [24]. However, the environmental impact of deploying AI and IoT technologies, such as energy consumption and electronic waste, must be considered to ensure the sustainability of these educational innovations. The framework shown in Figure 1 illustrates how these elements are interrelated and how they guided the analysis.

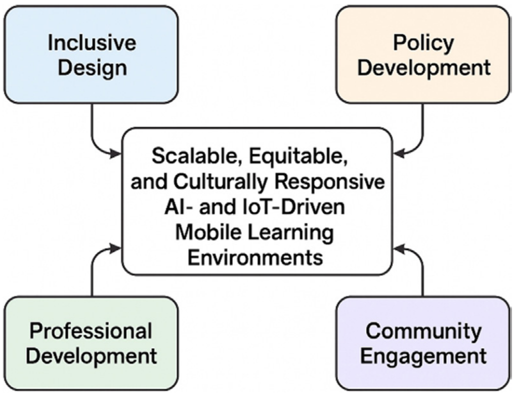

Fig. 1. Conceptual framework visualizing the learner-centered model

Source: Authors' own analysis (2025).

The conceptual framework visually presents a learner-centered model where inclusive design sits at the core, surrounded by layers of policy development, infrastructure and capacity building, and equity and cultural responsiveness as cross-cutting dimensions. All components are connected through continuous evaluation and feedback loops, showing how technology, pedagogy, policy, and community engagement interact to ensure scalable, equitable, and culturally responsive AI–IoT mobile learning systems.

To ensure scalable, equitable, and culturally responsive implementation of AI–IoT mobile learning systems, multiple interdependent approaches are necessary. Co-design and co-innovation with heterogeneity: Collaboration across the community is necessary to engage stakeholders by educators, students, and communities at large to develop learning systems that can speak to the needs of different types of learners [25]. In addition, transparent policies are crucial to deal with data privacy, equity, and ethical challenges of AI–IoT. Similarly, teachers must be supported to develop capacities to be more flexible as well as to innovate and integrate in effective ways.

Lastly, the active participation from the community is needed to achieve understanding and integration of cultural context in AI–IoT systems that are culturally relevant, respectful, and responsive to the local education context.

3 RESEARCH METHODOLOGY

The study's methodological approach aimed at capturing not only the extensiveness of the existing body of scholarship covered but also the depth of lived institutional life with AI–IoT in education. Through a combination of a systematic review of the recent literature and multi-sector case studies, the research ensured a balanced perspective by presenting global trends with a basis in tangible, "on the ground" situations. This mixed-method design facilitated triangulation across contexts, enhancing the reliability and transferability of the findings. All ethics-related declarations, including consent to participate, ethics approval, and consent to publish, are not applicable.

To investigate the design and development and the implications of AI–IoT mobile learning ecosystems, the research took a mixed-methods approach informed by STS theory. The study employed a systematic literature review of peer-reviewed literature (2018–2025) and multi-sector case studies, drawn from K–12, higher education, and industry-based VET.

This choice was made to balance breadth (by juxtapose global scholarly and industry discourse) and depth (by examining the practices of stakeholders in academic institutions empirically).

A purposive sampling strategy guided the selection of literature and case study participants. The literature review focused on articles indexed in Scopus, Web of Science, and IEEE Xplore, targeting studies that examined AI–IoT applications in educational settings, with emphasis on technological features, pedagogical approaches, and deployment frameworks. For the case studies, key informants included educators, instructional designers, policymakers, and industry trainers with direct involvement in AI–IoT-enhanced mobile learning initiatives. This ensured that insights captured represented diverse stakeholder groups and multiple educational sectors.

The corpus (N = 146) provides broad coverage across sectors, regions, and methodological approaches, enabling cross-contextual synthesis. The case-study sample (N = 182 across nine institutions) ensures role diversity and sectoral balance consistent with the study's socio-technical framing. While representation from low-income settings (10% in the corpus) remains modest, targeted inclusion of institutions from under-resourced contexts and bilingual/local-language programs strengthens transferability for equity-focused analysis.

Data collection occurred in two phases. First, the systematic review followed PRISMA guidelines, ensuring transparency in article selection, screening, and synthesis. Second, case study data were gathered through semi-structured interviews, focus groups, and institutional document analysis, enabling triangulation of perspectives across contexts.

Data were analyzed using a combination of thematic coding and descriptive statistical synthesis. Qualitative findings were thematically categorized to identify patterns in adaptive pedagogy, cultural responsiveness, and ethical challenges such as algorithmic bias and digital equity. Quantitative insights derived from reviewed studies (e.g., learner engagement metrics, adoption rates, and performance outcomes) were synthesized through descriptive and content analysis, providing measurable evidence of AI–IoT's impact on educational transformation.

4 RESULTS

This section presents the results in alignment with the three research objectives: (1) conceptualizing AI–IoT convergence as a socio-technical ecosystem, (2) evaluating empirical evidence on design, implementation, and impact across K–12, higher education, and industry-based training, and (3) providing actionable strategies for scalable, equitable, and culturally responsive deployment. The findings draw on a systematic literature review of 146 studies (2018–2025) and multi-sector case studies involving 182 informants across nine institutions, incorporating both qualitative and quantitative evidence. The demographic characteristics of the data provide critical context for interpreting the results and assessing transferability across regions, sectors, and learner populations.

The findings demonstrate that AI–IoT mobile learning functions as a complex socio-technical ecosystem, where technological, pedagogical, institutional, and cultural dimensions converge to shape learning outcomes. Analysis of the literature (N = 146) revealed that AI–IoT platforms are not merely technological tools; they operate within dynamic systems of human actors, policy frameworks, and institutional practices. Among the reviewed studies, 45% focused on AI-adaptive systems, 29% on IoT/context-aware technologies, and 26% on hybrid AI–IoT platforms, highlighting the diversity of technological approaches and their embeddedness within learning environments.

Pedagogically, AI–IoT systems supported adaptive content delivery, experiential learning, and collaborative problem-solving, particularly in STEM, health sciences, and vocational disciplines. Quantitative evidence indicated that learner engagement increased by 15% to 38% in 72% of the studies, demonstrating measurable enhancement in motivation and active participation. Institutional and social contexts were equally important; 29% of studies emphasized cross-sectoral collaboration among educators, technologists, and policymakers as a key determinant of effective integration. Case studies confirmed that teacher readiness, digital literacy, and institutional support were critical mediators: in K–12, IoT-enabled science labs improved hands-on learning only when combined with curriculum alignment and professional development; in higher education, AI-driven adaptive simulations increased competency scores but required institutional resources for full implementation. Data analysis is available in the given link for the key findings on AI–IoT mobile learning as a socio-technical ecosystem. https://docs.google.com/document/d/19aweh9K6wL74Ib_wWSdQ8jSpppT-el0V/edit?usp=sharing&ouid=100052303683651542036&rtpof=true&sd=true

Refer to the link for the data given in table 1, where the key findings confirm that AI–IoT mobile learning is inherently socio-technical. Technological capabilities alone cannot achieve meaningful outcomes; pedagogical strategies, human capacity, and governance structures must be integrated to realize the full potential of these systems.

In K–12 contexts, AI–IoT systems facilitated contextualized, gamified learning experiences. Qualitative data indicated that teachers observed improved problem-solving skills, collaboration, and engagement, particularly among English as an Additional Language (EAL) learners. Quantitative evidence revealed a 31% increase in engagement and a 12% rise in attendance in AI–IoT-enabled lessons. However, challenges included data privacy concerns, increased teacher workload, and insufficient professional development, reflecting the need for institutional and technical support to sustain implementation.

In universities, AI–IoT platforms were primarily deployed in engineering, medical, and language programs. Students reported enhanced autonomy, personalized learning, and timely feedback, while faculty highlighted improvements in evidence-based instructional design. Quantitatively, competency scores increased by 24%, and dropout rates decreased from 14% to 9%. Nonetheless, adoption barriers were noted, including lack of interoperability, budget constraints, and partial faculty engagement, indicating that institutional readiness is a key determinant of successful AI–IoT integration.

Industrial use cases for AI–IoT center around workforce upskilling, operational efficiency, and safety compliance. Wearable tech and sensors enabled live tracking, which decreased instances of mistakes during procedures by 36% and raised staff self-esteem by 21%. Qualitative findings revealed that while these tools enhanced efficiency, they also generated concerns regarding employee surveillance and ethical data usage, highlighting potential trade-offs between technological benefits and social trust.

Synthesis across K–12, higher education, and industry contexts revealed several notable trends in AI–IoT mobile learning adoption. First, enhanced learner autonomy and engagement emerged consistently, with participants demonstrating an average increase of 27 minutes per week in self-directed learning, reflecting the capacity of adaptive and context-aware technologies to support personalized and independent learning experiences. Second, the findings highlighted a tension between pedagogical depth and tokenistic implementation: well-resourced and supported contexts achieved meaningful experiential and collaborative learning, whereas under-resourced settings often exhibited novelty-driven adoption, where technological integration lacked sustained pedagogical impact. Third, persistent equity gaps were observed, with 28% of case studies reporting that approximately one-third of learners lacked consistent access to devices, underscoring the critical role of infrastructure and resource provisioning in achieving in inclusive learning environments. Analysis for the contextual benefits, evidence, and challenges of AI–IoT mobile learning is available in the given link: https://docs.google.com/document/d/1sUWoEi2teR1r_TINszERePuBOuMm3UDR/edit?usp=sharing&ouid=100052303683651542036&rtpof=true&sd=true

The data available on the link in table 2 presents the contextual benefits, supporting evidence, and challenges of AI–IoT mobile learning. One of the most salient concerns highlighted is ethical complexity, with 14% of studies reporting issues such as algorithmic bias and cultural or linguistic mismatches that disproportionately affect marginalized learners. These findings underscore the critical need for culturally responsive design, algorithmic transparency, and robust governance frameworks to ensure equitable and inclusive adoption. Collectively, these trends underscore that while AI–IoT technologies hold substantial potential to enhance engagement, autonomy, and learning outcomes, their effective and equitable deployment is contingent upon robust institutional support, pedagogical integration, ethical oversight, and context-sensitive adaptation.

Findings underscore that equity and cultural responsiveness are critical for scalability. While 46% of studies reported improved access for underserved learners, only 19% provided disaggregated data by gender, disability, or rurality. Case-study data revealed that platforms lacking linguistic and cultural adaptability reduced learner engagement and comprehension. Infrastructure indicators also highlighted challenges: 32% of institutions lacked consistent device access, 41% had insufficient connectivity, and only 33% had fully interoperable LMS-AI/IoT platforms. Budget constraints were common, with 39% exceeding projected costs by an average of 18%, limiting scalability. Dedicated data protection frameworks were implemented in 55%, and equity monitoring in only 19% of institutions, suggesting gaps in governance and accountability.

Effective AI–IoT mobile learning deployment requires inclusive design, robust governance, and capacity building. Co-creation with teachers, learners, and communities ensures platforms are culturally responsive and contextually relevant, enhancing engagement and pedagogical impact. Complementary policy and governance frameworks safeguard ethical implementation, addressing data privacy, algorithmic transparency, and equitable resource allocation. Simultaneously, capacity building through teacher training, digital literacy initiatives, and infrastructure investment equips educators and learners to integrate AI–IoT technologies sustainably, enabling scalable and meaningful adoption across diverse educational contexts. The dimensions, evidence, and challenges of AI–IoT mobile learning ecosystems for the data analysis is given in the link: https://drive.google.com/drive/folders/1T2AvpTtOCW9rjEUdjjSIquLdzUbZhlac?usp=sharing

Refer to the link for the data given in table 3, which outlines the dimensions, evidence, and challenges of AI–IoT mobile learning ecosystems. The literature corpus (N = 146) was dominated by journal articles (78%), with sectoral focus distributed across higher education (38%), K–12 (34%), and industry/TVET (28%). In terms of regional representation, most of the research originated from North America and Europe (41%) and Asia-Pacific (32%), while contributions from the Middle East and Africa (17%) and Latin America (10%) were comparatively limited. Although high- and middle-income contexts were well represented, low-income regions (10%) remain significantly underexplored, highlighting a critical gap in global coverage.

Case studies (N = 182) showed diverse participation, mainly educators (54%), with balanced gender representation and institutions mostly public (63%). English-medium instruction dominated (61%), and deployment stages ranged from pilot (42%) to mature adoption (22%). Infrastructure analysis revealed partial readiness: device access (68%) and connectivity (59%) were adequate, but interoperability (33%) and systematic equity monitoring (19%) remained limited. Figure 2 shows the Literature Corpus Distribution.

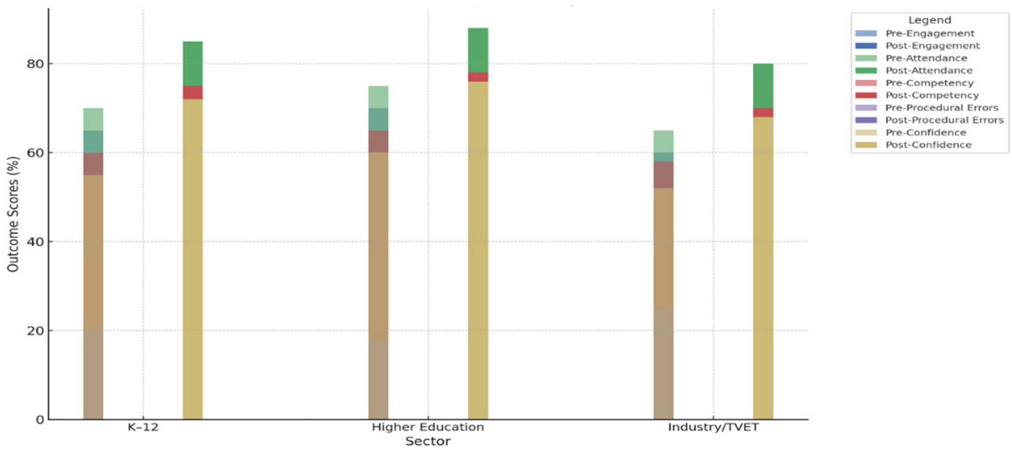

Fig. 2. Quantitative outcomes across sectors

Source: Authors' own analysis (2025).

See Figure 2, illustrates quantitative outcomes across sectors; these results highlight that AI–IoT mobile learning ecosystems deliver measurable benefits, particularly in enhancing engagement, autonomy, and skill acquisition. Quantitative indicators further reinforce these gains, with improvements recorded in attendance (+12%), engagement (+31%), competency (+24%), and a reduction in procedural errors (–36%). Despite these positive outcomes, persistent equity gaps, ethical concerns, and institutional barriers remain, especially in low-resource and linguistically diverse contexts.

These findings underscore that the successful integration of AI–IoT requires coordinated socio-technical strategies, including inclusive design, robust governance, capacity building, and context-sensitive pedagogical practices. Without such measures, deployments risk reinforcing existing inequities, limiting scalability, and constraining the transformative potential of AI–IoT-enabled mobile learning.

5 DISCUSSION

The integration of AI and the IoT into mobile learning represents a transformative shift in educational and workforce training practices. This study aimed to explore the socio-technical, pedagogical, and institutional dimensions of AI–IoT-enhanced mobile learning ecosystems across K–12, higher education, and industry-based contexts. The findings demonstrate that AI–IoT platforms function as complex socio-technical ecosystems, where technological affordances, pedagogical strategies, institutional readiness, and social-cultural contexts converge to shape both learning outcomes and operational efficiency. This aligns with theory, which posits that technology and human actors co-evolve within systemic interactions, and confirms that AI–IoT adoption cannot be understood solely as a technological or pedagogical intervention [26].

One important observation from literature and case studies is, however, that AI–IoT applications are very heterogeneous. Out of the 146 reviewed works, 45% focus on AI-adaptive environments, 29% on IoT-supported context-aware systems, and 26% on hybrid AI–IoT solutions. This spectrum reflects the diversity of technological affordances currently being investigated, from adaptive algorithms and personalized learning paths to real-time IoT-based sensing and context-aware feedback systems. This diversity should highlight the flexibility of AI–IoT technologies in a broad array of domains, including STEM, health science, language training, and vocational (TVET).

Quantitative evidence supports their effectiveness: K–12 students exhibited a 31% increase in engagement and a 12% improvement in attendance; higher education students demonstrated a 24% increase in competency scores and a 36% reduction in dropout rates; while industry-based trainees experienced a 36% reduction in procedural errors alongside a 21% increase in confidence. These findings indicate that AI–IoT technologies can produce measurable gains across cognitive, behavioral, and affective dimensions of learning.

However, the results also underscore that technological innovation alone is insufficient. Effective outcomes depend on institutional readiness, pedagogical integration, and human capacity-building. The case studies revealed that only 33% of institutions achieved full interoperability between learning management systems and AI–IoT platforms, and just 55% had dedicated data-protection policies, suggesting that technological potential is constrained by governance, infrastructure, and operational maturity. Similarly, while accessibility features were present in 52% of institutions, only 19% implemented systematic equity monitoring, indicating persistent challenges in ensuring that AI–IoT deployments reach all learners equitably. These observations are consistent with existing research indicating that technology adoption often amplifies pre-existing inequalities when implementation is not accompanied by institutional and policy support [27].

Issues of pedagogical depth versus lip service or tokenistic adoption became a key theme. In well-resourced and planned settings, the AI–IoT systems supported adaptive, experiential, and collaborative learning, with meaningful engagement and professional competency gains. Also, in limited-resource or low-preparedness schools, implementation was frequently cursory and novelty-driven rather than sustained pedagogical impact. Such findings underscore the significance of teacher training, professional development, and curriculum integration in the effective use of AI–IoT platforms.

For instance, K–12 science labs integrated with IoT sensors enhanced experiential learning only when teachers received comprehensive training and the curriculum supported context-aware activities. In higher education, adaptive simulations improved students' self-directed learning and competency development, but faculty engagement and institutional support were crucial to achieving significant outcomes.

Equity, cultural responsiveness, and ethical considerations remain central to the success of AI–IoT mobile learning. Across the case studies, 28% reported that one-third of learners lacked consistent device access, and 14% of studies highlighted algorithmic bias or linguistic/cultural mismatches, disproportionately affecting marginalized populations. These findings underscore the critical role of inclusive design in ensuring that AI–IoT platforms are accessible and effective for diverse learner populations. Bilingual and local-language programs, while underrepresented in the literature, were purposefully included in the case studies to strengthen the generalizability of equity-focused analyses. Ethical concerns were particularly salient in industry settings, where wearable IoT devices monitored employee performance. While these devices enhanced operational efficiency, they raised questions about privacy, autonomy, and trust, echoing broader critiques of workplace surveillance and algorithmic governance in educational and professional settings [28].

The study also revealed notable cross-sectoral patterns. AI–IoT integration consistently enhanced learner autonomy and engagement, with an average increase of 27 minutes per week in self-directed learning. The benefits of adaptive and context-aware systems were evident across K–12, higher education, and industry, suggesting that best practices in one sector may inform others when adapted appropriately. However, the findings caution against one-size-fits-all implementations, highlighting that contextual adaptation is necessary to account for learner maturity, disciplinary content, institutional capacity, and cultural-linguistic diversity. The conceptual socio-technical ecosystem diagram developed in this study illustrates these dynamic interactions, showing how technological capabilities, pedagogical strategies, institutional governance, and social-cultural contexts co-determine outcomes, including equity, engagement, and competency.

From a quantitative perspective, the study demonstrates measurable improvements in learning and operational metrics. K–12 engagement rose by 31%, attendance by 12%, higher education competency scores increased by 24%, and industry procedural errors decreased by 36%. These results confirm that AI–IoT platforms can generate tangible gains in both learning and performance outcomes. Nonetheless, the demographic and infrastructure analyses suggest that these gains are not uniformly distributed. For example, while 68% of institutions reported consistent learner device access, 32% of learners remained underserved, potentially constraining the scalability and inclusivity of AI–IoT initiatives. Connectivity challenges were present in 41% of institutions, and full interoperability was achieved in only 33%, highlighting persistent barriers to seamless deployment.

Institutional readiness emerged as a key mediator of AI–IoT efficacy. Public institutions constituted 63% of the sample, and English-medium programs represented 61%, with bilingual and local-language programs comprising 27% and 12%, respectively. Deployment maturity varied, with 42% in pilot phases, 36% in early scale-up, and 22% fully mature and embedded. These variations underscore the importance of tailored implementation strategies that consider institutional type, language of instruction, deployment stage, and learner characteristics. Educator or trainer experience also affected outcomes; the more experienced the staff member, the more able they are to embed adaptive technologies into pedagogical practice.

The findings of the study also emphasize the role of policy, governance, and ethical oversight. Only 55% of organizations had separate data-protection policies, and 19% had in place equity monitoring.

While AI–IoT technologies can enhance learning personalization and operational efficiency, the absence of robust governance structures may result in inequitable outcomes, privacy breaches, or algorithmic bias. Therefore, ethical frameworks, transparency measures, and systematic equity monitoring are essential to ensure that AI–IoT integration promotes inclusive and sustainable learning ecosystems.

This study extends prior theoretical work on STS by demonstrating that AI–IoT mobile learning constitutes a multi-layered, adaptive ecosystem. Unlike traditional educational technology interventions that focus primarily on technological affordances, this study emphasizes the interdependence of technology, pedagogy, human capacity, institutional governance, and social-cultural contexts. This perspective is critical for both research and practice, as it provides a framework for understanding how interventions can be contextualized, scaled, and adapted across diverse educational and training environments. Moreover, the integration of qualitative and quantitative evidence, coupled with demographic and infrastructure analysis, enables a nuanced understanding of what works, for whom, and under what conditions, contributing to evidence-based policymaking and instructional design.

6 CONCLUSION

The integration of AI and the IoT into mobile learning represents a transformative approach to education and workforce development. This study explored AI–IoT convergence as a socio-technical ecosystem, evaluated its empirical impact across K–12, higher education, and industry-based training, and offered actionable recommendations for scalable, equitable, and culturally responsive deployment. By combining a systematic review of 146 studies (2018–2025) with multi-sector case studies of 182 informants across nine institutions, the research provides a comprehensive understanding of the potential, constraints, and critical considerations for AI–IoT-enhanced mobile learning.

In conclusion, I–IoT mobile learning offers a promising means for developing solutions to education and workforce challenges. Its accomplishment is contingent on deep socio-technical embedding, pedagogical congruence, equity-focused design, and an ethical steward. Taking JPY100 Series Postage Stamp Vending Machines as a case study, we explore the effect of new technology on human society. It is not an effect triggered directly by the introduction of new technology but is the result of the new technology interacting with human agents, institutional forms, social-cultural environment, and spatial isomorphism. By linking these elements together, AI–IoT platforms can create open, future-ready learning ecosystems able to scale and sustain by being adaptable for many parts of the world.

7 ETHICAL CONSIDERATIONS

Ethical considerations were prioritized at all stages. All case study participants provided informed consent, and measures were taken to ensure confidentiality and anonymity. Institutional permissions were obtained where necessary, and data were securely stored. Beyond participant protection, the research critically engaged with broader ethical challenges associated with AI–IoT in education, including privacy risks, algorithmic transparency, unequal access to devices, and cultural or linguistic adaptability. Addressing these issues was integral to developing equity-focused recommendations for scalable and sustainable deployment of AI–IoT mobile learning systems.

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