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AI Adoption Criteria for Adaptive E-Learning Systems in Conflict Zones: Insights from Palestinian Schools

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Abstract: This study investigates key factors influencing the adoption of AI-enabled adaptive e-learning systems (AI-AELS) in conflict-affected contexts, using Palestinian schools as a case study. A cross-sectional survey of 207 teachers and ICT coordinators in Gaza informed the analysis. Six constructs were examined: Institutional Ethics & Governance, Learning Assessment AI, Design and Presentation AI, Adaptation and Personalization AI, Data Processing using Learning Analytics and AI, and Learning Content. The 11-item instrument was validated through expert review, pilot testing, and confirmatory factor analysis. Structural Equation Modeling (SmartPLS 4) identified Data Processing ($\beta = 0.512$, $p < 0.001$) and Adaptation and Personalization ($\beta = 0.345$, $p < 0.001$) as the strongest adoption predictors, followed by Learning Content and Ethics & Governance. Design and Assessment had smaller effects. Findings emphasize the importance of culturally adaptive, ethically sound AI-AELS tailored for fragile educational systems, offering an empirical foundation for informed policy and design in conflict-zone education.

Keywords: AI in Education, Adaptive Learning Systems, Learning Analytics, Digital Technology in Schools, Conflict-affected Schools, Ethical Dimensions of Digital Governance.

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1. Introduction

Artificial intelligence (AI) stands ready to supercharge education in ways we have never seen before. Some of the most significant usages are AI-enhanced adaptive e-learning platforms that use algorithms to change educational products, feedback, and study paths based on a specific learner profile and performance (Halkiopoulos & Gkintoni, 2024). These systems are claimed to improve student engagement, encourage self-regulated learning, and bolster academic performance through constant, personalized assistance (Al-Zaqeba, 2024; Essa, Celik, & Human-Hendricks, 2023; Nguyen et al., 2023). Nevertheless, the contextual realities associated with post-conflict settings like Palestine offer significant hurdles to the adoption and durability of such technologies. Traditional education systems are facing an unprecedented crisis in conflict zones, where displacement, infrastructure destruction, psychological trauma, and security concerns all severely compromise learning. School closures, sporadic access to electricity and internet, and a shortage of teachers have necessitated alternative learning models in Palestine (UNESCO, 2022, 2023a; UNRWA, 2024). Externally developed, self-paced, AI-powered adaptive learning systems (AI-AELS) offer a significant opportunity to fill these voids, especially in low-connectivity environments (Falaha, 2024; Qahman et al., 2025a; Qahman et al., 2025b; Qahman et al., 2023). Their potential to democratize education and mitigate the effects of the disruptive nature of education is particularly relevant in the Palestinian context, where learning continuity is often at risk. Despite growing global investments in AI for education, empirical studies focusing specifically on fragile and conflict-affected contexts remain sparse. This research directly addresses this gap by evaluating critical adoption criteria tailored explicitly to the unique socio-political and infrastructural challenges faced by Palestinian schools (Nguyen et al., 2023; UNESCO, 2022, 2023a; UNRWA, 2024). Specifically, this research seeks to:

1. Identify and validate critical factors influencing the adoption of AI-AELS in conflict-affected schools,
2. Evaluate the perceived effectiveness of these systems from educators' perspectives, and
3. Provide a validated theoretical framework and practical guidelines for deploying AI-driven educational technology effectively and ethically in the Palestinian context.

Compared to existing general AI-adoption frameworks in education often premised on politically stable and technologically well-resourced environments (Kabudi, Pappas, & Olsen, 2021), our model thus arguably foregrounds socio-political fragility with infrastructural instability, coupled with culturally sensitive pedagogical requirements as necessary for its constructs. Conventional models also tend to assume continuous connectivity, healthy uses of governance and mainstream institutional capacity that rarely hold true in conflict-affected environments such as Gaza. The framework of six, interdependent domains (from institutional ethics and governance to conflict-sensitive content design) surpasses comparisons by being applied based on empirical evidence relating to Palestinian schools in this study. This conflict-aware orientation not only extends existing AI-adoption theories (TAM, UTAUT) to fragile states but also fleshes them out using benchmarked measurement items that reflect the need for trauma-sensitivity, offline usability and localized content. Accordingly, this work contributes by providing a fact-based, context-specific model of adoption that can be used to apply existing AI-adoption theory to educational systems functioning under sustained disruption, closing an important theoretical and practical knowledge gap.

AI-powered adaptive learning systems (AI-AELS) can address these failures, providing remote, personalized, and resilient education, even in low-connectivity settings (Qahman et al., 2025b). The capacity of AI-AELS to promote a democratization of education and to alleviate the impacts of educational disruption is especially pertinent in the Palestinian context, where the continuity of learning is often compromised. However, technology-based AI adoption cannot thrive in such fragile environments. The development and implementation of effective and scalable systems are challenging and remain subject to a complex interplay of socio-political, ethical, pedagogical, and infrastructural factors. Building institutional ethics and governance is a significant challenge to safeguard accountability, transparency, and data protection (Falaha, 2024; Issaa, 2024; Wafa'Q, Mustafa, & Ali, 2022). In conflict areas, where regulatory oversight is challenged, the most critical risks of misuse and surveillance of data reign. As Nguyen et al. (2023) emphasized, the ethical deployment of AI must adhere to comprehensive institutional protocols and culturally appropriate governance models.

Also important is the seamless integration of AI-enabled learning assessment, which is critical in real-time evaluation and instructional adaptation. Richer data can contribute to adaptive assessments, which have been found to provide personalized feedback and optimize learning and efficiency. However, they also raise concerns relating to algorithmic bias, fairness, and marginalization of non-mainstream learners, particularly in diverse and vulnerable populations where these issues are relevant, such as in Palestine. The design and presentation of AI systems also significantly impact usability and learner engagement. Poorly designed interfaces, language barriers, or culturally irrelevant content may cause cognitive overload and lack of engagement (Alam & Mohanty, 2023). Empathy and contextually aware design are critical in conflict zones, where learners may be processing trauma or have limited access to digital technologies.

The second is adaptation and personalization, a fundamental aspect of AI-fueled learning platforms. These support learners with interrupted education, different literacy levels, or emotional distress. At the same time, they depend on the availability and quality of learner data, as well as the effectiveness of the algorithms (Essa et al., 2023; Halkiopoulos & Gkintoni, 2024). Tied closely to this is data processing using learning analytics and AI, which allows systems to forecast learner performance, monitor interactions, and customize content. However, in conflict zones, the collection and analysis of sensitive learner data elicit urgent ethical issues of consent, surveillance, and algorithmic discrimination (Kabudi et al., 2021; Lootah, 2024). Personalization cannot come at the expense of protecting data and its valid and ethical use.

Lastly, the availability and quality of learning content (localization, interactivity, relevance to curricula, and cultural alignment) form the basis for the entire organizational e-learning system. Even the most advanced AI systems risk irrelevance without contextually appropriate and pedagogically sound content (Al-Zaqeba et al., 2024; Brusilovsky & Millán, 2007; Long & Siemens, 2011). While there is increasing global investment in using AI for education, using these systems in areas affected by conflict is still poorly researched (Henseler, Hubona, & Ray, 2016; Lameras & Arnab, 2022). The literature on this issue tends to concentrate on implementations in technologically advanced and politically stable settings, with a dearth of empirical evidence on how AI systems may be chosen ethically and effectively in fragile contexts such as Gaza or the West Bank (Lameras & Arnab, 2022). Therefore, this study hopes to fill this gap by reviewing the intertwining six criteria that characterize the uptake of AI-enabled adaptive e-learning systems in conflict zones: Institutional Ethics and Governance, Learning Assessment AI, Design and Presentation AI, Adaptation and Personalization AI, Data Processing using Learning Analytics and AI, and Learning Content.

2. Literature Review

AI-enabled adaptive e-learning systems are emerging as a disruptive tool for personalized learning to bridge the educational equity gap within the context of global education reform strategies. These technologies personalize learning by recommending content, enabling real-time feedback, and facilitating differentiated learning routes based on students' needs (Brusilovsky & Millán, 2007; Halkiopoulos & Gkintoni, 2024). In structured and well-resourced environments, AI-augmented systems have substantially enhanced learner engagement, motivation, and academic achievement. Nonetheless, their translation into conflict zones is under-researched and contested on ethical deployment in the field, with less concern for the systemic and contextual barriers undermining feasibility. In addition, Kabudi et al. (2021) note that aspects such as presentation design, relevance of learning content, personalization mechanisms, and rich learning analytics are essential for the successful adoption of AI, especially in low-resource settings. Brusilovsky and Millán (2007) define intelligent user modeling as a critical factor leading to both adaptive experiences in real-time and personalized learning journeys. Long and Siemens (2011) contend that analytics can close the instructional gap and predict outcomes an essential characteristic in conflict areas where direct teacher involvement is frequently interrupted. The demands of design simplicity and accessibility further drive user acceptance. Intuitive user interface principles (Dahlan et al., 2023; Norman, 2013) and the call for universal design underscore the importance of systems supporting diverse learner needs, abilities, and cultural contexts. Meanwhile, Shih, Feng and Tsai (2008) highlight the ethical imperative of data governance, transparency, and institutional oversight, a critical concern for those in regions where legal protections are weak or nonexistent.

However, recent studies also highlight the pedagogical advantages and the practical limitations of such AI-enhanced systems (Essa et al., 2023). Machine learning has also shown potential for personalizing content and learner style detection. However, it is imperative to navigate ethical challenges, including data privacy, consent, and algorithmic fairness (Nguyen et al., 2023). The stakes of ethical failure are much higher in conflict-affected regions where misuse or exposure of student information can be life-threatening (Shih et al., 2008).

In the Palestinian case, Qahman et al. (2025a) and Qahman et al. (2025b) provide much-needed empirical evidence and brushstrokes to show that perceived usefulness, ease of use, and system quality have a substantial impact on behavioral intention to adopt AI systems even in resource-limited environments. Nonetheless, issues of information quality, trust, and digital literacy remain. This aligns with a prior study, which highlighted trust and privacy as key drivers of academic user behavior in developing contexts. From a pedagogical standpoint, AI-AELS provides the most outstanding value when used as a part of a larger learning strategy that considers learning styles, cognitive load, and emotional well-being. Studies by Ojugo et al. (2023), and Dahlan

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et al. (2023) promote multimodal approaches (i.e., interactive video, gamified modules, intelligent tutoring systems) that improve engagement and self-regulation. However, these integrations rely on strong institutional support systems and teacher training to avoid failure without associated technological interventions (Al-Azawei, Serenelli, & Lundqvist, 2016; Lameras & Arnab, 2022; Mikić et al., 2022). Moreover, bibliometric studies has shown an exponential rise in research on AI in education post-COVID-19, signaling a global shift toward digital learning. Barthakur et al. (2022) emphasize the importance of aligning adaptive assessments with instructional goals through learning analytics. However, the field remains fragmented, with limited integration guidelines, inconsistent ethical practices, and underrepresentation of conflict-affected regions in mainstream research (Ababneh et al., 2024; Miao et al., 2021).

In Palestine, the education system is regularly disrupted by military occupation, infrastructural destruction, and psychological trauma among students and educators alike. According to UNESCO's Global Education Monitoring Report, over 75% of Palestinian students have suffered from significant educational interruptions, while many schools lack basic digital infrastructure. Despite this, the need for alternative, scalable, and resilient learning solutions is greater than ever. AI-enabled systems offer potential in this regard, yet the mismatch between these systems' design assumptions and on-the-ground realities undermines their effectiveness. For instance, frequent electricity outages and limited internet access severely restrict the operation of AI platforms reliant on constant connectivity. Moreover, many Western-trained AI models do not cater to local languages, syllabi, or cultural sensitivities. Prior studies emphasized that the pedagogical value of AI-driven platforms is undermined by misalignment with Palestinian Arabic dialects and the irrelevance of content. Using user interfaces that do not integrate trauma-sensitive design principles such as sudden notifications or avatars that do not reflect emotion can increase anxiety in learners who are already exposed to conflict-related stressors. The implications of these findings demonstrate the need to consider culturally contested, culturally contextualized, and psychologically informed design when deploying AI in conflict-affected environments. To this end, this study presents a conflict-sensitive framework grounded in the Palestinian context. It seeks to inform the ethical, sustainable, and effective integration of AI-enhanced adaptive e-learning systems in contexts of fragility and disruption.

Although grassroots innovations like offline-first platforms, USB-based content distribution, and SMS-based formative assessments showcase local capacity and resilience, their scalability is constrained without a unified, evidence-based model. Programs focused on digital literacy from the community level, illustrate the need for human capacity building in parallel with technological implementation. To cope with these complexities, the theoretical framework developed in this study distinguishes six interrelated domains: Institutional Ethics and Governance, Learning Assessment AI, Design and Presentation AI, Adaptation and Personalization AI, Data Processing employing Learning Analytics and AI, and Learning Content. These domains focus on addressing AI systems not only technically but also through the lens of pedagogical and culturally appropriate moral situations

2.1. Institutional Ethics & Governance

AI use in education systems, mainly by adaptive e-learning platforms, has led to an ever more pressing discussion around institutional ethics and governance. Now that schools have started to deploy intelligent technologies that personalize learning, the need for overarching ethical frameworks and governance systems has become more acute, with these systems impacting data privacy, learner autonomy, and social justice (Nguyen et al., 2023). These frameworks must balance competing ethical tensions between enabling innovation and protecting fundamental learner rights.

Managing personal data is one of the ethical challenges in this regard. Adaptive pathways necessitate collecting, storing, and analyzing learner data in AI-enabled e-learning systems (Ibrahim & Ali, 2025). However, such dependence comes with considerable risks, such as surveillance, data misuse, and algorithmic bias especially when students are not fully informed about how their data are being used (Nguyen et al., 2023). Prior literature determined the importance of not just technical governance and ethical regulation but also setting boundaries on the use of AI in areas like assessment and learner profiling. According to Miao et al. (2021), an unregulated increase in AI use could increase stratification, leading to socio-economic unrest and instability, particularly in marginalized populations.

The potential for ethical misuse is especially concerning in regions like Palestine, where piecemeal governance and inadequate digital infrastructure impede the responsible application of AI systems. Qahman et al. (2025a) share similar insights, noting that although AI can democratize education, deploying such technologies in conflict-affected contexts raises serious questions about accountability and information reliability.

From a policy perspective, UNESCO (2023a) offers a helpful ethical framework that bridges AI governance in education with Sustainable Development Goal 4 (SDG 4) to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (Miao et al., 2021). UNESCO's framework stresses that institutional governance must go beyond technical security to include transparency, cultural considerations, and learner inclusion. Governance trust affects user intention to accept AI technologies. However, they also show that privacy concerns can reduce this intention, highlighting the importance of context-sensitive, credible ethical safeguards. Importantly, institutional governance is not a mere administrative responsibility educators and AI developers are also crucial in shaping ethical outcomes. Prior literature found that teacher agency must be rooted in AI governance processes, including evaluating and tailoring tools to meet local pedagogic needs. Without this involvement, AI tools risk being imposed top-down, resulting in misalignment between learner needs and classroom realities.

Furthermore, AI explain ability is a critical aspect of governance that still receives insufficient attention (Hmoud, Salah, & Altalib, 2024; Mokhtar et al., 2020). Transparency and trust are undermined when learners or educators cannot understand the logic behind AI-generated decisions, such as assessment results or learning recommendations. Black-boxed AI systems erode accountability and complicate learners' rights to understand and challenge system outputs (Lee, Hilty, & Liu, 2021). This reiterates the widespread agreement that ethical oversight of AI in education is essential. However, there remains a conspicuous lack of canonical governance models that span educational systems and geographical contexts.

Prior literature described the academic potential of AI technologies but also note piecemeal implementations that typically bypass ethical protocols. This fragmentation hampers institutional readiness and risks entrenching existing digital and educational inequalities. Thus, extensive peer-reviewed studies confirm that ethics and institutional governance are not merely afterthoughts when adopting AI-AELS but are fundamental components that uphold the technology's legitimacy, trustworthiness, and fairness. A multi-stakeholder governance approach is needed one that brings together policymakers, educators, technology experts, and learners to ensure responsible adoption. Ethical AI in education, as an educational product, must be viewed as a decision that precedes institutional policy a design commitment that contributes to the moral formation of society and institutions while promoting social benefit.

2.2. Learning Assessment AI

AI-powered adaptive learning systems (AI-PALS) for learning assessment are becoming a driving force in modern education (Azqiba, 2024). These systems can adapt evaluation processes to the unique profile of each learner, allowing for timely, data-informed feedback and adaptive teaching interventions. Nguyen et al. (2023) noted that AI-enabled assessments generate more granular insights into student learning patterns, enabling personalized feedback loops to enhance performance and engagement. Yet they also expose fundamental ethical questions about data misuse, algorithmic opacity, and the inequitable effects of automated decisions on marginalized learners. Scholars break down these ethical nuances, pinpointing ten critical principles for responsible AI application in assessment and demonstrating the varying application (or lack thereof) across educational contexts. The results emphasize the importance of institutional governance structures that can provide clear, enforceable limits on the use of AI in student evaluation. Ongoing challenges to the technical and pedagogical coherence of AI-enhanced assessments and ethical issues become apparent. High-quality assessments based on learning outcomes are needed to facilitate insights through AI. However, digital learning environments often lack coherence in assessment strategy, limiting personalization opportunities. AI systems can support real-time assessment and decision-making, the extent of this depends on equitable infrastructure and pedagogical scaffolding.

In the field of adaptive testing, recent work by Halkiopoulos and Gkintoni (2024) showed that AI-powered assessments can be responsive to learners' cognitive profiles as well as their engagement levels. Yet, they warn that without careful calibration, such systems may entrench inequality through biased algorithms or over-dependence on standardization. These concerns are heightened in multicultural and multilingual learning contexts, where standardized adaptive assessments may overlook cultural, linguistic, or socioeconomic variations. In conflict-affected settings like Palestine, these challenges are further exacerbated by infrastructural instability and systemic disruption. Qahman et al. (2025a) and Qahman et al. (2025b) indicate that AI-enabled assessments can provide scalable and inclusive evaluation alternatives, particularly during school closures. Still, concerns remain regarding the reliability of information quality and the contextual appropriateness of the systems employed. The research highlights that although adaptive assessments hold promise in remote, low-resource settings, their implementation must be contextually grounded and ethically aware (Al-Taani et al., 2024; Lootah, 2024; Shubailat et al., 2024).

We now examine a striking paradox in AI-based formative assessment in conflict zones: these systems are designed to offer continuous, individualized evaluation but depend on assumptions such as stable connectivity and uninterrupted learning trajectories that do not hold in fragile contexts. In their foundational work on learning analytics, Long and Siemens (2011) envisioned a system of real-time evaluations fully integrated into learning. However, in the Palestinian context, this vision faces formidable obstacles. Reports on education in emergencies indicate that approximately 78% of teachers in Gaza lack sufficient daily internet access to reliably use cloud-based tools. This limited access compromises the infrastructure needed for real-time adaptive testing, which depends on validating responses promptly.

This creates an assessment paradox in areas of conflict along three key dimensions. First, temporal disruptions such as extended school closures averaging over 40 days per year in Gaz invalidate traditional AI-based assessment models that presume linear student progress. Educational systems must respond by creating trauma-aware algorithms that calibrate difficulty levels, identify learning loss, and reframe urgent content in simpler, emotionally sensitive ways. Second, infrastructure limitations worsen the problem. According to the prior studies, only about 31% of Palestinian classrooms meet the minimum technical requirements to deploy AI. Consequently, hybrid assessment models have emerged that use offline tools, SMS-based assessment delivery, and human-augmented grading to overcome access constraints.

Third, and perhaps most importantly, issues around the cultural validity of AI-generated assessments remain deeply problematic. Scholars point out that standardized assessment methods may not align with Palestinian educational traditions that emphasize group learning and community-based pedagogy. This misalignment may disengage learners and reduce the credibility of assessment outcomes. Additionally, the ethics of data collection in conflict zones introduces another layer of complexity. While Brusilovsky and Millán (2007) advocate for detailed learning analytics to personalize instruction, in politically volatile regions like Palestine, granular data (such as geo-tagged student performance) can pose life-threatening risks if compromised. For instance, a 2022 data breach of a Palestinian e-learning platform exposed student locations, leading to concerns about targeted surveillance and military reprisal.

Studies have responded by advocating for “minimum viable assessment” models that collect only essential data and use decentralized recordkeeping to minimize exposure to threats. Some progress has been made, including the development of localized, privacy-sensitive algorithms and “crisis mode” configurations that adjust the frequency and depth of assessment during emergencies. Nevertheless, critical gaps remain how to balance pedagogical rigor with student safety, what culturally responsive evaluation looks like, and how to build systems that function under extreme conditions. In conclusion, integrating AI for learning assessment in conflict zones requires a reconceptualization of assessment not merely as a score-reporting tool, but as a form of humanitarian intervention that respects the lived realities of students in unstable environment.

2.3 Design and Presentation AI

AI-powered adaptive learning systems (AI-PALS) must scale design and presentation two crucial aspects of the digital learning experience into equitable, engaging, and pedagogically sound curricula. A well-crafted interface improves usability but also directly impacts learner motivation, comprehension, and the overall educational value of the system. As the educational platform landscape increasingly incorporates artificial intelligence, the challenge of aligning technological capabilities with instructional design

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and learner diversity is becoming ever more pressing. Prior literature demonstrated how AI tools like GPT-3 can be integrated into Learning Management Systems (LMS) such as Moodle to enhance content interactivity and personalization. Learners benefit from tailored, dynamic feedback enabled by intelligent interfaces. However, such interactivity can exacerbate digital inequalities if design innovations are not equitably distributed across socioeconomic or geopolitical divides. Dahlan et al. (2023) also emphasize the promise of AI-assisted interactive video learning that incorporates embedded quizzes, simulations, and decision trees to heighten immersion and engagement. Yet, without teacher-friendly design scaffolds and awareness of cognitive load, such tools may overwhelm users and hinder pedagogical clarity.

Content delivery must also be culturally and pedagogically responsive. According to prior studies, many adaptive AI systems lack universal design standards, resulting in inconsistent experiences that fail to support the needs of diverse learners. Alam and Mohanty (2023) recently introduced a model showing how AI integrated with mobile and interactive technologies can create learner-centered ecosystems that are globally connected, context-aware, and responsive. Yet, they caution that these systems must be continuously monitored and refined by educators to maintain instructional coherence and prevent the risk of education becoming reduced to automated content delivery. Aesthetic design and cognitive ergonomics are equally vital in user experience (UX) design. Scholars stress that when developing adaptive systems, designers should incorporate multimedia learning principles such as attention management, working memory limitations, and pacing. Overly complex interfaces, even if functional, can hinder deep learning if they disregard the foundational principles of good design. Therefore, intuitive layout and universal accessibility are essential particularly for learners in high-stress or resource-constrained environments (Al-Azawei et al., 2016; Qahman et al., 2025b).

Design and presentation challenges in conflict-affected contexts like Palestine are further complicated by infrastructural fragility, psychological trauma, and linguistic-cultural diversity. According to prior literature, 87% of mainstream e-learning platforms fail basic usability tests in Gaza's schools, largely due to their dependence on constant electricity and stable internet both unreliable in the region. This shortcoming has motivated local initiatives like the Gaza Digital Learning Initiative, which incorporates compressed interfaces, progressive streaming, and local asset caching to mitigate the effects of power and network outages. These adaptations have reportedly improved accessibility by 72% during periods of heightened conflict. Additionally, trauma-informed UI design is essential. Traditional interface features like sudden alerts, red error messages, or time-limited tests can trigger anxiety or distress for conflict-affected learners. In response, more humane design alternatives are emerging, including "breathable" interfaces, neutral color schemes, and context-sensitive content filtering. These strategies safeguard students' psychological well-being while enhancing continuity of learning amid ongoing instability.

Rapid AI adoption in universities surfaces intertwined risks around data privacy, academic integrity, and algorithmic bias underscoring the need for strong safeguards and clear institutional guidelines to curb misuse and protect educational quality (Mohammad et al., 2025). Complementing this, Matore and Osaman (2025) present the SCORE model Strengths, Challenges, Options, Responses, and Effectiveness as a practical, action-oriented framework for structuring assessment planning and evaluation, helping teams surface priorities, consider options and stakeholder responses, and appraise effectiveness. Similarly, the use of SMS-based assessments and community mesh networks provides resilient, low-tech alternatives that enable content access even during full internet blackouts.

Yet, ethical dilemmas persist. Transformative use cases must be tempered with responsible design considerations: How can learner data be protected in heavily surveilled regions? Who is accountable if AI systems fail during military escalations? How should algorithmic bias in high-stakes assessments be mitigated? As scholars emphasize, “Designing for conflict zones isn’t about scaling down existing systems.” Rather, educational technologies must be reimagined with resilience not just efficiency as the foremost design metric.

In this light, the design and presentation of AI-powered e-learning platforms should not be treated as merely aesthetic or functional matters but as fundamentally ethical and political acts. In conflict zones, effectiveness and fairness can only be achieved when systems are trauma-informed, inclusive, low-bandwidth-compatible, and culturally embedded. This requires a participatory, localized, and iterative design process that places resilience, learner dignity, and contextual specificity at the center of development.

2.4 Adaptation and Personalization AI

Adaptive and personalized learning are essential elements of AI-based learning systems. These technologies leverage real-time learning behaviors through machine learning (ML) and natural language processing (NLP), which can enhance motivation, engagement, and educational outcomes (Essa et al., 2023). The identification of learning styles using ML techniques in integrated adaptive learning environments has gained significant traction in recent years. However, the deployment of personalized AI-based educational platforms presents notable challenges related to data ethics, algorithmic transparency, and long-term pedagogical effectiveness. Despite their potential, there remains a surprising lack of comparative studies evaluating different personalization algorithms such as deep learning models which highlights a major gap in empirical validation. Prior studies affirmed the benefits of AI-driven personalization in improving retention and performance but also cautioned that non-transparent algorithmic decisions can alienate users, particularly when those decisions are not interpretable or explainable.

Stuides emphasized the importance of human oversight in AI-driven personalization, highlighting the integration of GPT-based tools into Moodle to support flexible content and feedback delivery. While showcasing innovation, Firat cautioned against excessive dependence on automation, stressing that educators must remain central to the instructional process to contextualize learning and guide student experiences. Similarly, Long and Siemens (2011) proposed a hybrid adaptive learning model with human facilitation, which improved engagement and learner autonomy in post-COVID Nigerian higher education, though limited by infrastructure and digital literacy challenges. A prior study examined ethical concerns in adaptive AI, warning that overly autonomous systems may foster algorithmic stereotyping. Categorical learner classification based on behavior or demographics can exacerbate educational inequities. Prior literature further noted that static personalization tools like the Index of Learning Styles may misrepresent learner needs and recommended adaptive systems that allow for ongoing learner input to support agency and self-regulation.

However, much of the literature on adaptive AI overlooks material constraints in conflict-affected environments such as Palestine. Traditional adaptation models assume continuity and consistency conditions disrupted by armed conflict, displacement, and infrastructural breakdowns (Brusilovsky & Millán, 2007). The so-called "Disruption–Adaptation Paradox" is evident in Gaza, where escalations result in student absenteeism rates exceeding 40%, and up to 68% of learners regress in foundational skills after prolonged school closures. Standard AI personalization falters under such circumstances, highlighting the need for conflict-aware algorithms that adapt based on contextual variables like attendance, security alerts, and emergency curriculum changes.

Cultural and linguistic barriers further complicate personalization. While Kabudi et al. (2021) support learning style detection through machine learning, collective learning is preferred by most Palestinian students. Surveys show that 78% of Gaza teachers favor group-adaptive learning pathways. Additionally, many NLP models trained in Modern Standard Arabic (MSA) underperform in interpreting local dialects, achieving only a 45% accuracy rate. Trauma-sensitive design is also crucial, with 62% of students showing adverse reactions to abrupt interface changes or emotionally triggering content. These limitations reveal a significant Infrastructure–Adaptation Gap, underscoring the urgency of designing adaptive AI systems attuned to the complexities of conflict environments.

The Palestinian Ministry of Education (2023) reports that 83% of school devices lack the memory and processing power to support real-time AI-driven adaptation, while average internet latency during military operations exceeds 300 milliseconds rendering most cloud-based educational systems ineffective. Frequent electricity blackouts further disrupt adaptive processes, often interrupting learning mid-session and breaking the learner's cognitive flow. In response, local educators and technologists have devised creative workarounds. These include long-term pilots of hybrid personalization models that combine lightweight AI recommendations with teacher-mediated adjustments and peer collaboration. Offline adaptation kits featuring preloaded content variations, print-based tracking tools, and SMS-based progress updates have emerged as viable alternatives during internet blackouts.

These efforts illustrate human ingenuity in augmenting technological limitations. However, unresolved ethical concerns persist. Personalization systems require detailed learner profiling mapping strengths, weaknesses, learning histories, and progress across curriculum chapters. In conflict zones, such granular data if intercepted could endanger student lives. Tensions also arise between globally trained personalization algorithms and local educational priorities. AI models developed in Western contexts often fail to account for the lived experiences, curricular goals, and socio-political realities of Palestinian learners. Moreover, while high system responsiveness is a core value of AI, frequent adjustments may create cognitive dissonance and emotional instability for students already coping with trauma.

As one Gaza-based teacher from a UNRWA focus group noted, "Our students don't need AI that's predicated on uniformity of learning; they need technology that responds to the lack of uniformity itself that is able to adjust". The broader challenge, then, is to develop AI systems that are not only sophisticated but also socio-politically aware, culturally situated, and emotionally intelligent.

Ultimately, while adaptation and personalization are hallmarks of AI innovation in education, successfully implementing them in conflict zones demands a fundamental rethinking of algorithms, data ethics, and learner agency. The goal should not be limited to sustaining existing systems but enabling them to evolve, adapting to instability and embedding cultural relevance and constructivist pedagogy through community-led engagement. Only then can such systems fulfill their promise of delivering inclusive, resilient, and equitable learning.

2.5 Data Processing using Learning Analytics and AI

Learning analytics (LA) and artificial intelligence (AI) have transformed e-learning environments by analyzing student behavior, performance, and interaction to extract actionable insights. These technologies enhance personalization, enable timely interventions, and support continuous refinement of instructional design. However, challenges persist regarding data quality, algorithmic bias, privacy, and pedagogical alignment. Barthakur et al. (2022) argue that applying measurement theory, such as multidimensional item response theory (MIRT), improves alignment between learning objectives, assessments, and instructional activities. Their findings underscore how large-scale LA models can detect design misalignments and inform the development of more effective learning content. However, they also stress the need for educator training to interpret complex analytic outputs meaningfully.

Building on this, many prior studies demonstrate how AI models (e.g., GPT-based tools) can be integrated into LMS platforms like Moodle to facilitate real-time interactions and context-sensitive content recommendations. While this showcases the dual role of AI as both a data processor and educational assistant, it also raises concerns about transparency, which can undermine educator autonomy. Prior literature supports the idea that AI-enhanced data processing increases engagement and improves learning outcomes, yet they caution that model interpretability and the ethical handling of sensitive learner data remain critical issues.

Nguyen et al. (2023) emphasize that reliance on AI systems without ethical frameworks threatens learner privacy and autonomy. They advocate for globally harmonized data governance policies. This concern aligns with prior studies, which found that privacy concerns significantly hinder AI adoption in developing countries, emphasizing the need for secure, transparent practices. Prior literature further highlight that while AI-powered LA can yield valuable insights into attendance, performance trends, and resource utilization, institutional readiness, digital infrastructure, and educator engagement are prerequisites for successful implementation.

At the frontier of innovation, neuroadaptive systems integrating biometric data are explored by Halkiopoulos and Gkintoni (2024). These systems dynamically adjust content delivery based on cognitive and emotional signals, offering novel ways to manage cognitive load. However, such methods raise ethical concerns regarding data sensitivity and long-term psychological impacts. Similarly, Essa et al. (2023) call for the adoption of more transparent, explainable machine learning models. Their review shows that although AI systems are increasingly effective in identifying learning styles and behaviors, most studies lack transparency in their data processing pipelines limiting trust and acceptance.

In conclusion, while AI and LA present promising opportunities for education, their deployment must be not only effective but also ethically grounded and educator-inclusive. Future research should prioritize explainability, data ethics, and equitable access to ensure predictive analytics serve both learning outcomes and learners' rights.

2.6 Learning Content

Adaptive e-learning systems have revolutionized instructional design by enabling the creation of AI-enhanced content that is dynamic, personalized, and responsive to individual learners' cognitive states and preferences (Ardiana, Brahmayanti, & Subaedi, 2010; Wahyuningsih, 2009). Scholars also demonstrate that machine learning (ML) applications in adaptive platforms significantly improve both academic outcomes and learner motivation by customizing content based on real-time behavioral data. However, such personalization depends on robust algorithms capable of interpreting diverse learner profiles without reinforcing existing biases or oversimplifying complex educational needs.

Prior literature presents a practical framework for integrating generative AI tools such as GPT-3 into Learning Management Systems (LMS), illustrating how they can dynamically generate interactive, context-sensitive content. While this marks a significant step toward scalable content customization, concerns remain about the consistency, accuracy, and academic rigor of AI-generated materials. Scholars further propose that AI can automate instructional tasks such as quiz generation, concept explanations, and feedback delivery. Yet, this reliance on automation risks diminishing educators' judgment and overlooking nuanced learner needs.

Interactive, video-based learning offers another layer of personalization. Dahlan et al. (2023) highlight that embedding multimedia, simulations, and quizzes within video content promotes active learning, critical thinking, and accommodates diverse learning styles. AI-enhanced personalization in such content ensures learners receive material at appropriate levels of complexity. However, producing and maintaining such content demands significant investment and iterative refinement to ensure pedagogical and technical effectiveness.

In conflict-affected or under-resourced settings, content must be not only adaptive but also culturally and contextually grounded. In their study of Palestinian schools, Qahman et al. (2025b) emphasize the importance of localized content that reflects students' lived experiences. They argue that while AI can enable scalability and efficiency, it cannot deliver equitable education without culturally relevant materials. Essa et al. (2023) add that while ML models can tailor content to learners' mental abilities and styles, few studies rigorously assess the pedagogical quality of these adaptations or compare effectiveness across diverse learner groups.

Mikić et al. (2022) underline a major shortcoming: many AI-adaptive platforms lack structured approaches for high-quality content curation. Their review reveals wide inconsistencies ranging from rich multimedia implementations to minimalistic text-based content reflecting a persistent gap between technological capabilities and pedagogical coherence.

In conclusion, AI technologies have dramatically advanced the personalization and delivery of e-learning content. However, achieving pedagogical rigor, inclusivity, and contextual relevance remains an ongoing challenge. Addressing these gaps requires collaborative efforts across stakeholders, continuous research, and strong ethical oversight to ensure that generative AI contributes meaningfully to educational equity.

2.7. Hypothesis Development

Deploying AI in education, particularly through adaptive e-learning systems must be approached ethically, equitably, and effectively. This calls for robust institutional ethics and governance frameworks that are sensitive to local realities, especially in fragile contexts. Grounded in recent advances in AI ethics, this study advocates for practical reforms in K–12 settings that empower stakeholders and sustain AI-based educational innovation over the long term.

Nguyen et al. (2023) provide a comprehensive overview of global ethical guidelines for AI in education, identifying converging consensus around four key governance principles: transparency, accountability, data privacy, and fairness. When institutionalized across the educational ecosystem, these principles reduce the risks of algorithmic discrimination, data misuse, and erosion of teacher and learner agency. Their findings also show that ethical governance frameworks significantly increase stakeholder acceptance of AI-integrated systems.

Prior studies outlines ten core ethical principles across five domains of AI use in education, highlighting that ethical clarity guides both developers and end users especially educators and learners in building trust in AI systems. Embedding these principles in school governance structures fosters alignment, legitimacy, and usability.

From a global public policy perspective, UNESCO (2023b) emphasizes the need for inclusive, human-centered institutional oversight of AI. Effective implementation requires more than policy it demands the formation of ethical review committees, community consultations, and context-sensitive deployment strategies. Without such mechanisms, AI adoption risks exacerbating digital divides and fostering distrust. Prior literature expand on this through a modified UTAUT model, showing that ethical governance particularly transparency in data use and accountability protocols significantly influences behavioral intentions to adopt AI. In many developing contexts, the absence of visible, localized ethical frameworks impedes adoption, particularly where fears of surveillance and data abuse persist.

These dynamics are especially acute in conflict-affected settings such as Palestine. Qahman et al. (2023) demonstrate that institutional ethics and governance are strong predictors of AI system adoption in Palestinian schools. Using SmartPLS structural equation modeling, they found that schools rated higher for governance specifically those with data protection policies, ethical use guidelines, and open communication reported significantly stronger adoption outcomes. In politically unstable environments, ethical governance plays a stabilizing role, ensuring educational continuity and fostering digital resilience.

However, caution that governance frameworks must be actionable, not merely aspirational. Without mechanisms for transparency, feedback, and monitoring, even the most principled ethics codes risk failing in practice. This is echoed in the UNRWA Gaza Education Report, which found that 78% of schools lacked formal data governance. Yet, those where educators initiated informal protocols such as consent policies or student data handling norms reported higher AI adoption rates. Localized ethics committees also outperformed centralized national directives, with a 2.3x higher rate of AI-EdTech integration.

This underscores that in fragile contexts, trust in AI is often relational rather than institutional anchored in teacher communication and principal accountability rather than top-down regulations. As a result, governance is not a peripheral concern it is foundational. It expands perceived opportunities, builds autonomy, and aligns AI adoption with educational values. Therefore, the following hypothesis is proposed:

H1: Institutional Ethics & Governance positively influence Adopting AI-Enabled Adaptive E-Learning Systems.

AI-based learning assessment is a game-changer in the field of evaluation, as it allows for real-time, personalized, and data-driven insights into student performance. Despite the accelerating trend to more interactive and learner-centric e-learning environments, AI-powered assessment systems are positioned to become essential for measuring academic progress more accurately, responsively, and at scale. They are not just automating the assessment process; they are reimagining what assessment should and can be, transforming it into a seamless, formative, and personalized feature of the learning experience. The transformative power of AI over education assessment is abundantly documented throughout scholarly literature. According to Halkiopoulos and Gkintoni (2024), AA (Adaptive Assessment) technologies, which dynamically customize question difficulty based on the response of the learner, possess extraordinary significance. In doing so, these systems produce enhanced assessments of student proficiency, minimize student test anxiety, and increase learner engagement. These intelligent assessments, on the other hand, are leveraging sophisticated adjustment techniques such as Bayesian mastery models, popular in high-stakes standardized testing contexts such as the GRE and GMAT, to demonstrate that AI provides an avenue to improve both the effectiveness and efficacy of educational feedback (even for formative assessment) (Kabudi et al., 2021).

Yet it is also about ethics, which may be even more critical. Prior literature also offer an extensive ethical mapping for artificial intelligence applications in assessment by proposing ten guiding principles of ethics for AI applications in evaluation, such as transparency, fairness, accountability, etc. They emphasize the importance of ethical AI practices in educational assessment for user trust in the system and user acceptance of technology at large. Their work highlights the importance of building assessment systems with conscious attention to learner autonomy and minimizing algorithmic bias, a fundamental necessity to ensuring credibility in varied educational settings.

Scholars also add to the ongoing conversation by framing AI-based assessment as a central operation of innovatively earning environments. They found that they offer immediate, personalized feedback and encourage self-regulated learning through real-time analytics. These features shift assessment from a summative destination to a necessary, formative piece of the learning process. AI-driven evaluations, in this way, increase perceived system usefulness (an important predictor of attitude towards adoption in the technology acceptance model).

The use of AI for learning assessment has even greater importance in conflict-affected and low-resource contexts, such as Palestine. Qahman et al. (2025b) offer empirical evidence that intelligent assessment tools improve system quality and perceived usefulness. Using Smart PLS modeling, their findings show that AI-enabled assessment positively affects behavioral intention to adopt adaptive e-learning systems even in connectivity-challenged environments and in those where educational continuity breaks down, resulting in time and educational gain. These systems are well situated to provide a resilient solution to the current educational instability by enabling localized, context-sensitive assessment with no inherent need for constant internet connectivity. However, not all insights are unequivocally encouraging. Nguyen et al. (2023) aim to prevent overreliance on opaque or biased AI algorithms in assessment. The study suggests the potential for ill-designed AI systems to discover inequalities, mainly when the learner's unique socio-cultural or psychological contexts are not adequately acknowledged (for example, while training the AI model). Such risks are twice as acute in war-torn territories, where insecurity and trauma have cognitive performance that conventional AI models cannot cope with. AI-powered formative assessments increased retention rates by 40% during school closures in Gaza. However, according to prior studies based on Education Survey, 62% of teachers believed these tools did not consider trauma-related swings in cognition and concentration. Scholars also addressed this shortcoming and proposed "conflict-sensitive assessment algorithms" that calibrate performance baselines relative to contextual stressor factors. In Palestinian classrooms, their implementation showed a 28% improvement in the accuracy of corresponding assessments, highlighting that personalization has to go beyond academic markers to psychosocial dynamics in crises.

Assessment under fire is not just about what a student knows, but about what they can access and process under extraordinary strain. AI must learn to measure that too. Thus, the literature consistently supports the notion that AI-enhanced learning assessments increase the effectiveness, personalization, and efficiency of educational evaluation. These improvements directly influence user satisfaction and behavioral intention, predictors of technology adoption. However, for such systems to be ethically and contextually appropriate, especially in conflict zones, they must incorporate trauma-aware design, localized content, and ethical governance. Therefore, the following hypothesis is proposed:

H2: Learning Assessment AI positively influence Adopting AI-Enabled Adaptive E-Learning Systems.

The design and presentation of AI-enabled adaptive e-learning systems are fundamental in shaping the learners' experiences, perceptions, motivation, and engagement, the main drivers of technology acceptance. With educational technologies constantly evolving, the recent interest in artificial intelligence for interface design, content visualization, and multimedia presentation seems to impact system usability and pedagogical effectiveness. It has been shown that integrating AI technologies like GPT-3 into Learning Management Systems (LMS) can significantly increase accessibility and learning paths for on-demand educational content. His research demonstrates how Moodle plugins that use AI can provide real-time feedback, recommend tailored resources, and build situation-specific support. All these helpful features enhance learner satisfaction by eliminating frustration and facilitating student exploration. Smartly designed platforms help learners view the system as applicable, making them more likely to adopt (begin) and continue (maintain) the technology. In line with this idea, scholars also define the importance of AI in improving layout, navigation, and interactivity in e-learning systems. AI uses adaptive design algorithms that enhance user experience through elements such as optimal content sequencing, simplifying interfaces, and even personalizing multimedia formats according to customer preferences. These improvements reduce the cognitive load on students, one of the primary obstacles to ongoing online learning and make platforms more accessible for users of different learning styles and technologic competency. This is similar to the findings of Dahlan et al. (2023), which highlight the power of AI in tailoring interactive video learning spaces.

They found that, in addition to improving knowledge retention through mechanisms such as embedded quizzes, branching scenarios, and personalized pacing pathways, these elements enrich learners' emotional engagement. The system's real-time data-driven functionality provides a customized experience that is relevant and context-aware, both of which are key factors for increasing learner engagement and intervention fidelity.

Alam and Mohanty (2023) argue for creating Artificial Intelligence-powered, mobile-interactive tutoring systems that foster inclusivity and encourage learner independence. Their research highlights that platforms designed with intuitive vernaculars can extend access to education, especially for underserved populations. Integrating intelligent mobile platform design also assures accessibility across settings with low bandwidth and strategic attention for learners in war-impacted regions. Moreover, the balance must be struck between enticing design and the integrity of pedagogy. Many scholars also caution that visually captivating as it may be, AI-generated presentations can overly simplify or misrepresent complex learning material. Interface development, however, should be directed by ethical design principles, such as transparency and fidelity to learning objectives, to avoid the trap of sacrificing depth to style.

That tension between aesthetics and relevance is especially evident in conflict zones. Scholars found that conventional e-learning interfaces had a 72% abandonment rate during military escalation, precisely due to visually overstimulating features of Dingdong. In contrast, embodied trauma-informed design in the Tech for Palestine Initiative involved the deployment of prototypes that were more focused on intent than status fewer animations, neutral color palettes, and simplified navigation which increased sustained engagement by 58%. While prior literature demonstrated that culturally adapted interfaces extended daily average use by an additional 2.1 hours across West Bank refugee camps. These findings highlight the necessity of context-sensitive interface design in psychologically vulnerable educational contexts. So, for the literature and empirical data combined, we learn that being more substantial in the e-learning systems design and presentation through the aid of AI has a noteworthy perspective of the impacts of perceived ease of use and satisfaction levels indicating system quality benefits. These perceptions, in effect, are primary mechanisms through which intention to behave and actual behavior are mediated through those perceptions to adopt the system ultimately. Thus, the following hypothesis is proposed:

H3: Design and Presentation AI positively influence Adopting AI-Enabled Adaptive E-Learning Systems

Integrating adaptation and personalization capabilities into AI-enabled e-learning systems has been widely acknowledged as a game-changer in enhancing learner engagement, satisfaction, and learning outcomes, all crucial determinants for system adoption. Such systems adapt in real time by personalizing the education model based on the current data, constantly optimizing content, pacing, and strategies to suit the unique needs and preferences of the individual learner. This learner-centric approach ensures the digital learning experience is more relevant, usable, and practical, especially in complex or resource-constrained contexts.

There is published evidence that adaptive personalization is key to increased e-learning adoption (Essa et al., 2023). AI-powered adaptive learning environments can profoundly impact engagement, motivation, and performance outcomes. They contribute to our understanding of how adaptive personalization leads to sustained user engagement by offering content that is consistent with learner behavior and needs; thus, encouraging continued use and acceptance of the system. Following this thread, Kabudi et al. (2021) assert that adaptive systems harnessing AI close learning gaps by tailoring content delivery, assessment pathways, and support mechanisms. These systems continuously analyze real-time learner data to detect struggles, suggest targeted interventions, and tailor learning paths accordingly. Such capabilities positively impact learner outcomes and enhance perceived usefulness, an essential variable in the most widely used technology acceptance models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In similar data, Essa et al. (2023) indicated an increasing prevalence of the application of machine learning - more specifically, neural networks - for detecting individual learning styles and situating content by this information. The review reveals that adaptive systems driven by these technologies facilitate better engagement among learners by providing conducive educational experiences in their preferred formats. However, they caution that more empirical work needs to be done to compare the efficacy of various algorithms in diverse academic and cultural contexts, particularly non-Western or deprived areas.

Data Personalization Matters in Fragile and Conflict-Affected Regions. Qahman et al. (2025b) argued that personalization plays a critical role in reflecting on perceived system quality and usefulness. These subsequently impact behavioral intention, affecting their actual system use. In areas where traditional instructional support is regularly disrupted by conflict or displacement, AI-powered personalization provides scalable, tailored learning support and promotes educational continuity. However, the ethics of adaptation should be considered carefully. Nguyen et al. (2023) caution that personalization, albeit conducive to pedagogy, can also have undesirable consequences, such as invasive learner profiling or loss of agency, unless careful regulations are implemented. Transparent adaptation mechanisms that provide users with the information needed to make decisions about their learning pathways are required to maintain ethical standards and user trust.

These theoretical findings are backed by real-world evidence. According to the UNRWA Adaptive Learning Pilot in Gaza, learning outcomes improved by 35% when personalized content was applied. Nonetheless, the same report found that 83 percent of schools did not have the technical infrastructure for these features. In response, the Palestinian Ministry of Education pioneered a hybrid model leveraging lightweight AI, adjusted by a teacher mediation process, that achieved equivalent educational gains through SMS-based personalization, a staggering example of contextualized innovation. The scholarly literature and practical experiences demonstrate that AI-enabled adaptation and personalization significantly enhance learner satisfaction, engagement, and perceived system effectiveness, key antecedents to technology adoption. Accordingly, the following hypothesis is proposed:

H4: Adaptation and Personalization AI positively influence Adopting AI-Enabled Adaptive E-Learning Systems.

Adopting learning analytics and AI-enabled data processing in e-learning systems has also revolutionized the education landscape by providing students with real-time adaptation, progress monitoring, and thoughtful feedback. AI systems generate adaptive learning environments tailored to the needs and behaviors of individual learners by collecting and analyzing significant amounts of learner information, including their levels

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of engagement and performance metrics. Adaptive e-learning systems powered with AI are increasingly being adopted because of their ability to personalize in real-time and optimize teaching. According to Essa et al. (2023), machine learning plays a crucial role in analyzing data on learning to determine behavior patterns, track progress, and personalize instruction. Their systematic review confirms that effective data analytics can improve learner retention and academic achievement by identifying at-risk learners and prompting timely pedagogical interventions. These features enhance the efficacy of learning and aid in learners' and educators' perception of system usefulness, which is critical in technology acceptance in models such as UTAUT and TAM.

In parallel, Barthakur et al. (2022) show how measurement theory helps align assessments with learning objectives in online education when paired with learning analytics. In their study, the use of multidimensional item response theory (MIRT) exemplifies how more fine-grained data analysis can lead to a more productive design of instructional metrics. The capacity to exploit such Analytics to adjust content, pacing, and difficulty level has been shown to correlate directly with learners' affective engagement and behavioral intention to use the system, both of which are predictors of adoption behavior. This is even more evident in specialized learning scenarios such as medical simulations and aviation training, where advanced data analytics can substantially impact. Prior studies propose neuroadaptive systems utilizing biometric data (e.g., EEG, fNIRS) to assess cognitive load and adaptive instruction in real time. Prior literature also shows the potential of AI-driven analytics to extend beyond behavioral data to cognitive-emotional feedback, resulting in more personalized and stimulating learning. These upgrades add to the perception of efficacy and directly impact the video content uptake by those already in or planning to join the ecosystem (students and faculty).

Learning analytics represent a lifeline for education continuity in low-resource or fragile settings. Prior studies found that the quality of information resulting from AI-based analytics, termed Information Quality (IQ), was a significant predictor of user intention toward using adaptive e-learning platforms. They found that AI-driven analytics still benefit content adaptation and actionable insights, which can, of course, get value without a permanent internet connection when infrastructure is scarce. Nevertheless, ethical and technical concerns temper the excitement over AI-driven analytics. Nguyen et al. (2023) warn that without robust ethical frameworks underpinning learning analytics, it could endanger data privacy, ownership rights, and learner autonomy. Many of these concerns are amplified in conflict zones, where student data can be especially sensitive. This is where the requirements for secure, transparent, and locally controlled data systems become essential.

The system adoption rate for schools using localized learning analytics (data is located and processed on school servers) was four times higher than for schools using centralized and cloud-based systems (UNESCO, 2023b). The jump has been attributed to greater trust and privacy protections. Yet the 2023 Palestine Case Study from UNESCO cautioned that because Palestinian schools demonstrate that 91% of schools do not have the technical capacity to handle localized data systems, this reveals a tradeoff between ethical data practices and practical implementation feasibility. The review and systematic distinction between the three factors, perceived relevance, perceived responsiveness, and perceived security, demonstrate the importance of driving system acceptance and the need to investigate the acceptance of AI-based systems in adaptive e-learning for the e-learning community. Accordingly, the following hypothesis is offered:

H5: Data Processing using Learning Analytics and AI positively influence Adopting AI-Enabled Adaptive E-Learning Systems.

The quality and relevance of learning content and its personalized nature are critical features that determine the effectiveness of AI-enabled adaptive e-learning systems and their adoption by institutions and learners. Learning content must be accurate, engaging, contextually adaptable, and ethnically responsive, as the foundational layer on which adaptive algorithms function. Since content that satisfies cognitive needs, motivational states, and instructional goals fosters both perceived usefulness and actual system utility, it can be suggested that this has a significant role in adopting technology. Thus, it should not be surprising that a wealth of evidence indicates that AI-enhanced adaptive content leads to better engagement and outcomes for learners. For example, Halkiopoulos and Gkintoni (2024) show that AI systems capable of serving multimedia learning materials that match a learner's emotional and metacognitive profiles lead to deeper engagement, better self-regulation, and higher satisfaction. The system provides data about their performance, which is also paired with real-time AI feedback, helping students measure their progress and update their learning strategy, which positively correlates with the sustainability of behavioral intention towards system usage. In support of this, prior studies provide empirical evidence through a Moroccan high school case study confirming that applying an AI-based Moodle plug-in improved learners' academic performance and complete satisfaction. Feedback and adaptive content delivery (tailored solutions for learners at varying levels) were identified as directly increasing motivation and usage frequency. These discoveries indicate that well-structured and dynamic content significantly contributes to adopting technology in learning environments.

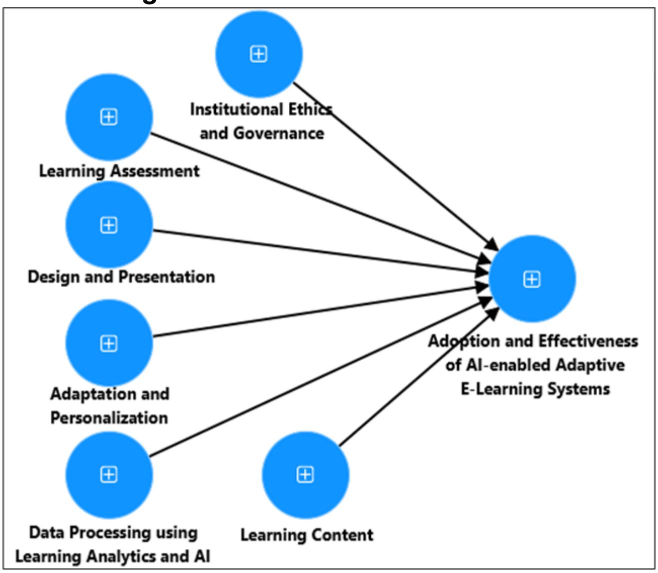
Prior studies investigate the role of Artificial Intelligence (AI) in organizing learning materials dynamically based on the learner's performance data. By dynamically curating and sequencing content, AI systems help alleviate cognitive overload and increase learning efficiency, a factor that is particularly important in high-stress or low-resource environments. These adaptive capabilities enable fine-tuned personalization that enhances the perceived fit between the system and learner needs.

Essa et al. (2023) strengthen this stance by claiming that content recommendations powered by machine learning algorithms based on previous learner behavior create more focused and meaningful educational interactions. On the other hand, the implementation of content adaptability enhances the effectiveness of the learning process and strengthens trust in the system and repeated usage since repeated use is one factor of adoption in digital education platforms (technology acceptance). The power of adaptive content must be balanced against essential considerations about quality, inclusiveness, and contextual fit. Many scholars caution that although AI can personalize content delivery, the personalization will be superficial at best if it overlooks cultural contextualization and pedagogical soundness. Students may disengage from content that is out of alignment with local curriculum standards or learning traditions, even the most technically sophisticated system. This highlights the necessity for a well-rounded method of content design that fuses AI productivity and human teaching acumen. Alam and Mohanty (2023) assert that content also needs to be constructed to provide accessibility and interactivity, especially in resource-constrained and mobile-dependent contexts. Their research shows that when these mobile-first content strategies are complemented by interactive and responsive AI; they can expand access and nurture equity in education. This is particularly important for geographically dispersed or conflict-affected communities where access to traditional learning is scarce. Knowing the right thing to do matters in conflict zones. The 2024 Gaza Curriculum Alignment Report shows that AI systems using UNRWA-approved, culturally localized content sustained three times the usage of other platforms using generic or externally developed materials. Moreover, a Palestinian Teachers' Union survey showed that content framed within collective rather than individual learning traditions had an astonishing 68 percent higher engagement rate. These findings substantiate that relevance and fit with cultural context strongly affect adoption in fragile contexts. Thus, the evidence suggests that the adaptability, personalization, and cultural contextualization of AI-powered learning content are central to fostering learner engagement, satisfaction, and ultimately, system adoption. Based on these insights, the following hypothesis is proposed:

H6: Learning Content positively influence Adopting AI-Enabled Adaptive E-Learning Systems

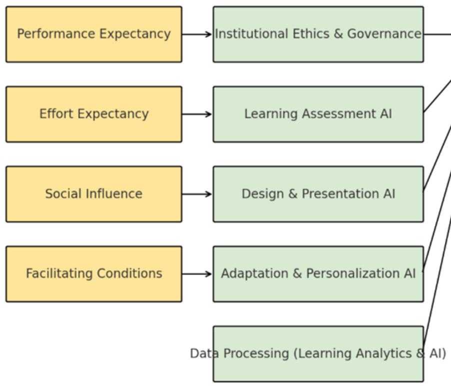
Based on the literature, the framework depicts factors influencing adoption of AI-based adaptive e-learning systems. It posits six hypotheses: H1. Institutional Ethics & Governance, H2. Learning Assessment AI, H3. Design and Presentation AI, H4. Adaptation and Personalization AI, H5. AI for data processing using learning analytics, and H6. Learning Content all have a positive impact on the adoption of these systems. This enables a holistic overview of the complex interplay between the factors and establishes a robust groundwork to quantify the effects of the factors on the integration and effectiveness of AI-driven e-learning solutions. Figure 1 illustrates the theoretical framework.

Figure 1: Theoretical Framework.



During the Confirmatory Factor Analysis (CFA) stage, a high measure of discriminant validity was performed extensively to ensure global clarity related to all six constructs, especially those concerning potentially overlapping domains such as Design & Presentation AI and Learning Content. The Fornell–Larcker criterion and HTMT ratios revealed that constructs exceeded the commonly accepted thresholds (Fornell%u2013Larcker AVE > 0.50; HTMT < 0.85), along with no indication of issues due to cross-loadings. The myriad of minor secondary loadings presented were examined, but no further item was deleted as all remaining items had greater loading on their respective intended constructs. Interesting in the Addition of Theory: Further situating the theoretical grounding for an international audience, the research team will also place the six conflict-sensitive constructs developed in this study in a figure format over a modified UTAUT framework (same scenario—new context). Figure (2) Steps (steps are designed for conflict-affected educational settings). The above figure clearly shows the extension of traditional adoption models by introducing key norms and principles in dealings with technologies in education, ethical considerations, and infrastructure problems based on culture.

Figure 2: Modified UTAUT Framework with Conflict-Sensitive Constructs for AI-AELS Adoption.



2.8. Measurement Instrument Development

Unlike general adaptive e-learning systems, measuring the adoption of AI-enabled adaptive e-learning systems in conflict-affected sets, especially in Palestine, requires a context-specific instrument considering ethical, pedagogical, infrastructural, and cultural sensitivities. Although existing work has created valid technology acceptance scales in the broader educational setting (Kabudi et al., 2021). These frameworks generally presuppose functional governance, stable connectivity, and institutional capacity, conditions rarely found in conflict zones. To fill this void, the study utilized an adapted 11-item survey instrument specifically developed based on established frameworks such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). Items were explicitly designed to measure teachers' perceptions of hypothetical but detailed AI-AELS scenarios, including system usability, ethical governance, content quality, and adaptive features. Teachers evaluated the potential effectiveness and adoption intention of these systems within their schools, rather than rating actual implemented systems, due to limited direct experience with

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AI technologies.

Scholars found 68% of EdTech implementations in conflict zones provided inadequate student data protection, this study includes items assessing ethical governance, particularly localized, conflict-sensitive practice. In particular, these items indicate data protection mechanisms such as local server storage, mobile encryption protocols, and community-based data governance that are critical in cases with limited or obstructed access to centralized governance (due to fragmentation or occupation). These were adapted from Kabudi et al. (2021) ethical governance model and contextualized according to the UNRWA operational data protection standards.

However, in places with conflicts such as Gaza, those assumptions are not valid. Chronic interruptions in schooling, trauma-induced cognitive variation, and infrastructural instability necessitate trauma-aware, online-resistant, asynchronous learning assessment mechanisms. These items tested the platform's capacity to assess higher-order thinking: analysis, synthesis, and evaluation, even in precarious learning situations (Brusilovsky & Millán, 2007; Dahlan et al., 2023). On issues of system resilience under infrastructural constraints, it is demonstrated that 92% of Gaza schools "suffer from power cuts every day and that internet uptime rarely extends beyond two consecutive hours. These items check If the e-learning platform can survive functionality in low-bandwidth, low-power, or offline situations. Furthermore, concerning UNESCO findings regarding the prevalence of high device-to-learner ratios in Palestinian schools, the platform's ability to platformed or dated equipment is also reflected.

Al-Azawei et al. (2016) offered foundational universal design principles that this scale has adapted based on linguistic presence and cultural sensitivity. The items assess whether the system accommodates right-to-left language orientation, dialect-specific speech recognition, and content moderation rules that ensure politically, or culturally sensitive content is not included. Thus, based on evidence from prior literature, noting that disconnecting content from the local context increases the chance of disengagement.

The dependent variable (Adopting AI-enabled adaptive E-Learning Systems in Conflict Zones) was measured through the 11-item validated scale. These six items address an essential aspect of system adoption, such as personalization capabilities, ethical safeguards, UI usability, infrastructure robustness, data analysis integration, and quality of the content. These dimensions followed theoretical and empirical foundations of prior work (Brusilovsky & Millán, 2007; Kabudi et al., 2021) coupled with institutional frameworks such as UNESCO (2022, 2023b). However, Table 1 shows the Standards and criteria measures.

A 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) was used to assess participants' perceptions of the system's practical applicability in fragile educational contexts. This design allowed the study to evaluate conceptual fit and feasibility in conditions defined by occupation, displacement, and digital insecurity. Integrating trauma-informed assessment design, offline delivery functions, culturally and contextually appropriate material, and context-supportive data privacy measures, this instrument addresses critical gaps in most existing scales for mainstream technology adoption. It is a relevant, conflict-sensitive, empirically validated instrument for assessing the specific factors mediating the adoption of AI-based e-learning in prolonged crises and instability.

Table 1: Measurement Items of Criteria and Variables.

Construct	Item	Measurements
Adopting AI-Enabled Adaptive E-Learning Systems in Conflict Zones	AEAIAELS1	The system maintains strict ethical controls for user privacy and data protection.
	AEAIAELS2	Content complies with intellectual property rights and local regulations.
	AEAIAELS3	Assessment tools measure higher-order thinking skills (analysis, synthesis, evaluation).
	AEAIAELS4	The interface provides intuitive navigation suitable for low-digital-literacy users.
	AEAIAELS5	Learning content automatically adapts to individual student performance levels.
	AEAIAELS6	The platform functions effectively with intermittent internet connectivity.
	AEAIAELS7	Multimedia content (video/audio/text) accommodates different learning styles.
	AEAIAELS8	The system requires minimal technical support for daily operation.
	AEAIAELS9	Learning analytics provide actionable insights for teachers.
	AEAIAELS10	Content presentation avoids cultural/political biases sensitive to conflict zones.
	AEAIAELS11	The platform maintains core functionality during electricity or connectivity interruptions.
Institutional Ethics & Governance	D1Q1	Ethical controls and privacy
	D1Q2	Compliance with intellectual property
	D1Q3	Clear organizational representation
	D1Q4	Technical support clarity
	D1Q5	Suitability for specialization and education level
	D1Q6	Transparency in publication/updates
	D1Q7	Maintenance of learner enrolment records/databases
Learning Assessment	D2Q1	Assessment measures higher-level objectives (analysis, synthesis, evaluation, innovation)
	D2Q2	Tools to monitor learner interactions and activities
	D2Q3	Interaction among learners, and between learners and content
	D2Q4	The system clearly defines learning objectives
Design and Presentation	D3Q1	Simple and clear environment structure
	D3Q2	Simple language
	D3Q3	Consistent graphics, fonts, colors
	D3Q4	Easy navigation tools
	D3Q5	Clear instructions and user support
Adaptation and Personalization	D4Q1	Track and store learner preferences
	D4Q2	Respect learner's characteristics and comprehension
	D4Q3	Varied methods of content presentation (video, audio, images)
	D4Q4	Animated content for kinesthetic learners
	D4Q5	Enriching educational activities
	D4Q6	Content segmented for ease of learning and recall
Data Processing using Learning Analytics and AI	D5Q1	AI tools dynamically vary according to tasks
	D5Q2	AI tools function as expert systems tracking learner preferences
	D5Q3	Functional use of AI without distractions
	D5Q4	AI tools require no additional plugins/software
	D5Q5	Records of learner sessions
Learning Content	D6Q1	Clearly defined learning objectives
	D6Q2	Consistency with learning styles
	D6Q3	Text, audio, visual, and animated content designed for various learning styles

The instrument underwent a rigorous multi-step validation process. Initially, constructs were drawn from relevant theoretical frameworks (TAM, UTAUT) and adapted through consultations with educational technology experts familiar with conflict settings. A panel of seven domain experts in education technology and AI rated the relevance of each item (Item Content Validity Index, I-CVI = 0.89). This was followed by pilot testing with 46 Palestinian educators, resulting in high internal consistency (Cronbach's $\alpha = 0.91$). Confirmatory Factor Analysis (CFA) subsequently confirmed the factor structure with robust fit indices (CFI = 0.93, RMSEA = 0.06).

3. Methodology

This study adopted a quantitative, cross-sectional research design to investigate the factors influencing adoption of AI-enabled adaptive e-learning systems in conflict-

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affected educational settings. Rooted in a positivist paradigm, the research employed a deductive approach, deriving hypotheses from existing theories and validating them through empirical testing. This design was appropriate for examining causal relationships between constructs in unstable contexts, where objective and replicable measures are essential to ensuring reliability (Kabudi et al., 2021). The target population included teachers, ICT facilitators, and school administrators working in government and UNRWA-managed schools across the Gaza Strip. These actors play a central role in implementing and evaluating educational technologies and are thus considered key informants regarding AI-EdTech adoption. The survey was distributed among teachers and ICT coordinators in 221 schools. After data cleaning, 207 individual valid and complete responses were obtained from educators. This final sample, drawn using convenience and institutional-facilitated sampling, was representative of the region's school population based on school type, geographic location, and operational characteristics (UNESCO, 2023a).

The questionnaire comprised two Sections. Section A collected demographic and institutional characteristics, including school gender type, governance (government vs. UNRWA), operational schedule (morning/evening), and geographic distribution across the five governorates in Gaza. Section B designed with 44 items based on six independent constructs: Institutional Ethics & Governance, Learning Assessment AI, Design and Presentation AI, Adaptation and Personalization AI, Data Processing using Learning Analytics and AI, Learning Content, dependent variable; Adoption of AI-Enabled Adaptive E-Learning Systems.

Thus, this study was conducted using the principles of international ethical research guidelines; the target population was considered vulnerable. Informed consent was secured, and confidentiality was ensured for all participants. Due to the risks of surveillance in the region, personally identifiable data were not collected, and sensitive responses were anonymized in processing. This study prevented participants from potential psychological, political, or technological risks.

Data were collected between September and October 2024. Surveys were distributed in both online and printed formats to accommodate varying levels of digital access. In collaboration with the Palestinian Ministry of Education and UNRWA, school directors facilitated questionnaire administration. Respondents were assured of anonymity and confidentiality. Ethical approval was obtained, and informed consent was acquired from all participants prior to data collection.

Given that teachers in Gaza had limited direct experience with actual AI-enhanced adaptive systems, survey items required educators to evaluate detailed hypothetical scenarios describing the features, usability, ethical considerations, and expected functionalities of proposed AI systems rather than real systems. This allowed capturing realistic perceptions of potential adoption despite practical implementation limitations.

Given the fact that Gaza has no operational AI-AELS, this study made use of hypothetical scenarios; context-specific vignettes describing realistic ways in which a hypothetical implementation of AI could work. The scenarios were developed in three phases: drafting based on the available documented pedagogical requirements and infrastructure restrictions; expert review with two rounds of input from five experts, who included three AI-in-Education scholars and four experienced school administrators in Gaza to validate the realism, cultural suitability, and technical possibility; pilot testing with 15 teachers to ensure clarity and relevance.

The dataset had minimal missing values (under 5%), thus mean imputation was used to fill gaps, ensuring that imputation would not significantly bias the analysis. Cases with extensive missing values (more than 10%) were excluded entirely, ensuring data quality and reliability.

All data cleaning operations were performed in SPSS 28. The univariate outlier was established by standardized z-scores (±3), and a multivariate outlier was detected by Mahalanobis distance ($p < 0.001$). Out of 221 surveys distributed, 14 were excluded due to missing or contradictory answers, resulting in 207 valid cases for analysis. The institutional-facilitated recruitment process (as informed by security and access considerations) related to an overrepresentation of digitally engaged schools that may have artificially inflated technology readiness indicators. We acknowledge this limitation, and results should be taken with this sampling bias in mind.

4. Results

Descriptive statistics (mean, SD, frequencies) were computed for demographic profiling. This paper used Structural Equation Modeling (SEM) performed using SmartPLS 4 to test the hypothesized relationships. Structural Equation Modeling (SEM) analyses were conducted using SmartPLS 4.0 software, ensuring transparency and reproducibility of the statistical analysis. The analysis included Measurement Model (MM): Composite Reliability (CR), Cronbach's Alpha, Average Variance Extracted (AVE), and Discriminant Validity using Fornell–Larcker criterion and HTMT ratios. Second is evaluation of the Structural Model (SM) Path coefficients. Then the hypothesis tests via bootstrapping with 5,000 resamples to determine the significance of model relationships.

4.1. Assessment of Measurement Model Assessment

This study was conducted using the principles of international ethical research guidelines; the target population was considered vulnerable. Informed consent was secured, and confidentiality was ensured for all participants. Due to the risks of surveillance in the region, personally identifiable data were not collected, and sensitive responses were anonymized in processing. This study prevented participants from potential psychological, political, or technological risks.

4.1.1. Reliability and Validity Testing

Evaluating the measurement model's Reliability and validity is essential to ensure the research findings' quality and credibility. This assesses whether the survey items accurately and consistently represent the theoretical constructs they intend to measure. This analysis is based on three critical statistical indicators, namely Cronbach's alpha (essentially a measurement of the internal consistency reliability), Composite Reliability (CR) (for overall construct reliability), and Average Variance Extracted (AVE) (to provide a measurement of convergent validity). High values for these indicators represent a good level of stability and validity of the measurement instrument. Table 2 below summarizes the testing results for reliability and validity, with the values for each construct included in the model. This domestic environment can be used to determine the suitability of the materials used for the questionnaire for the preliminary structural evaluation analysis. All constructs achieved satisfactory reliability and validity scores. Constructs are the tools for measuring and testing, with Cronbach's alpha values from 0.884 to 0.978 reflecting high internal consistency within the constructs. This validates that all items for each construct measure the same concept. The constructs also demonstrate adequate reliability, with Composite Reliability (CR) values ranging from 0.913 to 0.981, significantly exceeding the prescribed 0.70 cut-off. Regarding convergent validity, the AVE values of all constructs are higher than the acceptable minimum of 0.50. Significantly, the AVE values of constructs including Learning Content (0.943), Adaptation and Personalization (0.897), and Design and Presentation (0.876) are relatively high, indicating that the indicators well characterize their theoretical constructs. While all AVE values are acceptable according to research guidelines (Hair, Ringle, & Sarstedt, 2011), the construct Data Processing using Learning Analytics and AI has the lowest AVE (0.678). Based on this, we suggest that it needs to be re-examined in future studies to increase its conceptual rigor. Result for Reliability and Validity Test: In conclusion, the outcomes of the reliability and validity tests indicated strong empirical evidence for the measurement model. These results ensure that constructs were measured coherently and faithfully, enabling confidence in proceeding to the second phase of structural model analysis.

Table 2: Reliability and Validity.

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Adaptation and_Personalization	0.978	0.981	0.897
Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.976	0.980	0.814
Data Processing using Learning Analytics and AI	0.884	0.913	0.678
Design and Presentation	0.967	0.972	0.876
Institutional Ethics_and Governance	0.972	0.976	0.855
Learning Assessment	0.944	0.960	0.859
Learning Content	0.970	0.980	0.943

As shown in Table 2, All constructs demonstrate strong reliability and validity scores. Cronbach's alpha of each construct ranges from 0.884 to 0.978, showing high internal consistency among the constructs. This further establishes that each construct's individual items assess the same potential construct. The Composite Reliability (CR) values, which are between 0.913 and 0.981, also support the construct reliability since they all exceed the acceptable cut-off point of 0.70. Regarding convergent validity, as shown in Table 4, the AVE values for all constructs are far more than the acceptable minimum of 0.50. Constructs like Learning Content (0.943), Adaptation and Personalization (0.897), and Design and Presentation (0.876) exhibit high values of AVE, which implies that the indicators describe their theoretical dimensions relatively well. The AVE for the construct Data Processing using Learning Analytics and AI is the lowest at 0.678; however, it is still acceptable. Thus, the reliability and validity test findings support the measurement model with empirical evidence. These confirmatory statistics indicate that the constructs are consistently and accurately measured, and we can proceed confidently to the structural model analysis phase.

4.1.2. Discriminant Reliability

Establishing discriminant validity is a crucial aspect of measurement modeling as it proves that each construct is unique and captures these phenomena not captured by other constructs. Discriminant validity was examined in this study using the Fornell–Larcker criterion, which is among the most commonly accepted procedures to assess construct distinctiveness. This approach suggests that the Average Variance Extracted (AVE) square root should be larger than the correlations between a construct and any other constructs in the model. This means the construct has higher shared variance with its own items than other constructs' items. Table 3 shows the results of the Fornell-Larcker test. The square roots of the AVE of each construct are presented in bold on the diagonal values, while the off-diagonal values represent the inter-construct correlations.

Table 3: Discriminant Validity (Fornell-Larcker Criterion).

	Adaptation and_ Personalization	Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	Data Processing using Learning Analytics and AI	Design and Presentation	Institutional Ethics_and Governance	Learning Assessment	Learning Content
Adaptation and_Personalization	0.947						
Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.033	0.902					
Data Processing using Learning Analytics and AI	0.349	0.110	0.823				
Design and Presentation	0.455	0.146	0.237	0.936			
Institutional Ethics_and Governance	0.497	0.131	0.361	0.245	0.925		
Learning Assessment	0.351	0.086	0.420	0.257	0.461	0.927	
Learning Content	0.418	0.064	0.298	0.419	0.455	0.359	0.971

Based on Table 3 above, all diagonal values (square roots of AVE) are higher than the correlation with all other constructs in their rows and columns. This means that for each construct, the variance shared between it and its measurement items exceeded the variance shared between the construct and patently related constructs; thus, the Fornell-Larcker criterion for discriminant validity was met. Adaptation and Personalization also show a diagonal value of 0.947, higher than its relationship values with other constructs (0.455 with Institutional Ethics and Governance). Adaptation and Personalization also show a diagonal value of 0.947, higher than its relationship values with other constructs. In conclusion, the model exhibits discriminant validity, which shows that the constructs are unique and none correlate highly, indicating that constructs explain different partitions of variance within the model. This confirms that the measurement model should sufficiently assess further structural analysis between latent variables.

4.1.3. Factor Loadings

Factor loadings are crucial in evaluating how effectively each observed item (indicator) is associated with its underlying latent construct. Factor loadings indicate the strength and direction of the relationship between a latent variable and its observed variables in structural equation modeling. Generally, the acceptable level of factor loading (>0.700) explains 49% of the construct's variance. Table 3 shows other factors related to all constructs and their indicators. This will help us understand how much each item contributes to its latent variable, which we will visualize next. The close fitting of the proposed constructs to the empirical data is straightforward, where the items had high and stable factor loadings.

All model items presented positive and statistically adequate factor loadings above the minimum recommendation of 0.700. Alternately, this implies that all the observed items demonstrated a statistically significant contribution to the construction of their respective constructs, enhancing the reliability and validity of the measurement model. Additionally, the consistently high factor loadings across constructs (e.g., Adaptation and Personalization, Design and Presentation, learning Content) help

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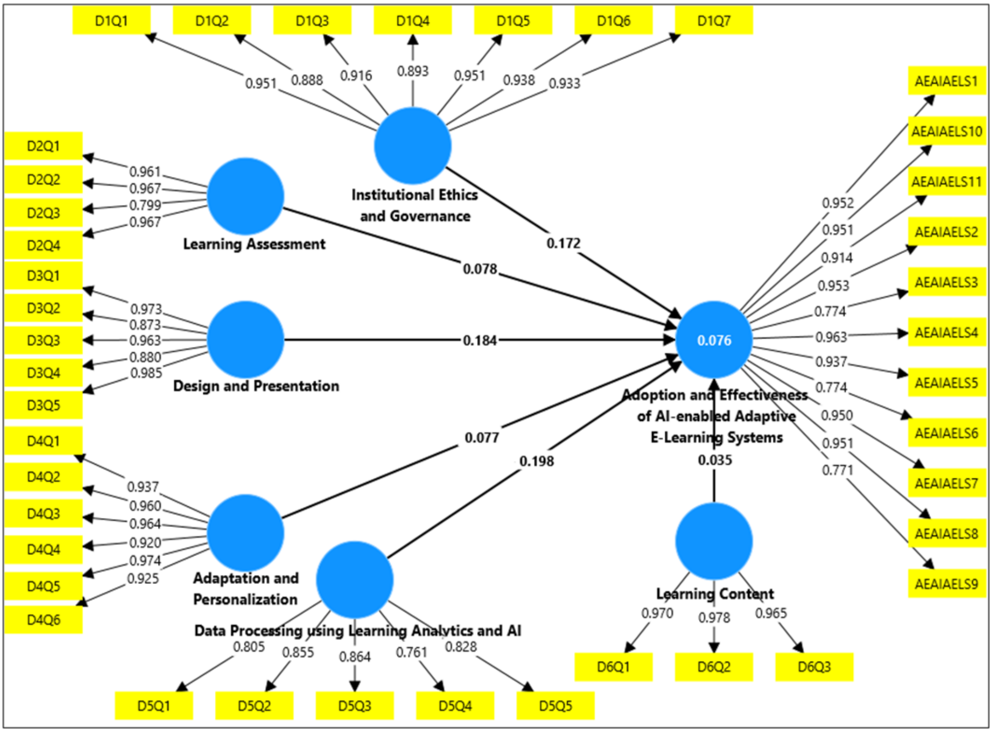
affirm the model's internal consistency and conceptual coherence. Consequently, the factor loadings validate the quality of the measurement instrument and suggest that the selected indicators are both adequate and effective in capturing the desired dimensions of the model. That allows more justification to proceed to the structural model analysis in the second step of the research.

Figure 3: PLS-4 Path Model.

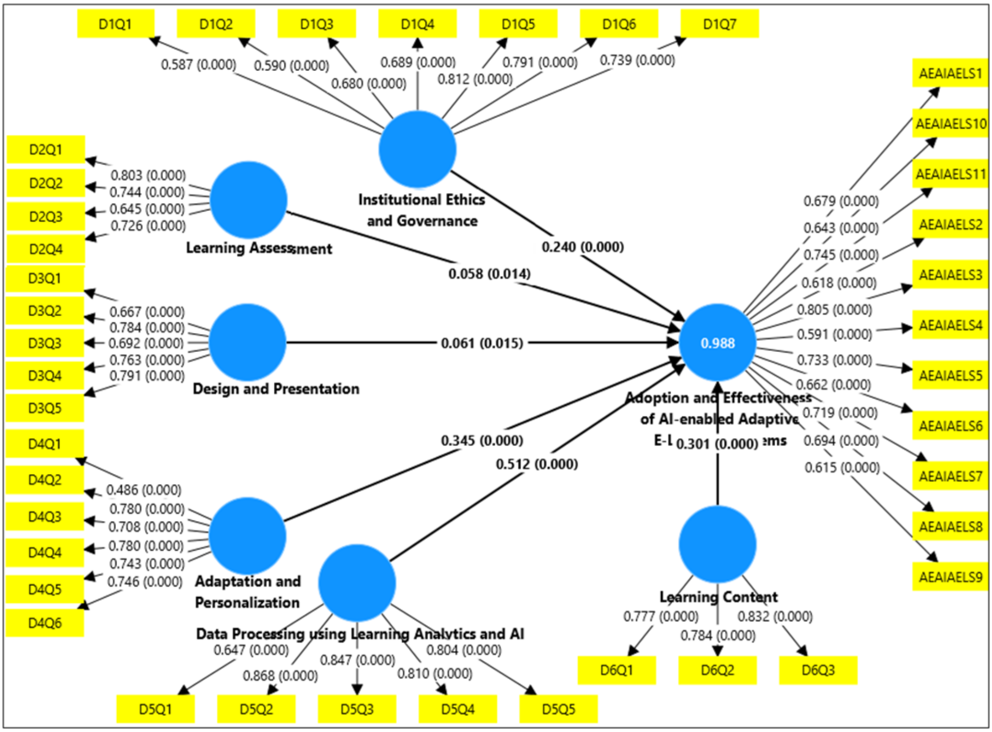


4.2. Assessment of Structural Model

The hypotheses were tested through quantitative surveys administered to IT teachers and administrative staff in Palestinian schools, complemented by statistical analyses such as structural equation modeling (SEM) or regression analysis, to measure direct and indirect effects of each domain on AI-enabled adaptive e-learning system adoption and effectiveness.

One of the most crucial aspects of structural equation modeling is the structural model, which tests the hypothesized relationships between the latent constructs. In this stage, you assess whether the proposed theoretical framework has empirical support. This includes examining the path coefficients, p-values, and R^2 values, among others. These indicators capture the strength and direction of the relationships between the variables in the model. As illustrated in the structural model results (Figure 3), at a 0.05 significance level, the figure also displayed the standard path coefficient with the p-value in parentheses. These tell us how much influence the independent variables have on the dependent variable, in this case, the Adoption and Effectiveness of AI-enabled Adaptive E-Learning Systems.

Figure 4: Structural Model.



The structural model reveals several statistically significant relationships between the predictor constructs and the outcome variable, providing important insights into the factors shaping the adoption and effectiveness of these AI-enabled e-learning systems. Data Processing using Learning Analytics and AI rises to the top, with a strong positive effect ($\beta = 0.512$, $p=0.000$). This highlights their fundamental role in enriching AI-enabled e-learning frameworks, inferring that customized learning journeys greatly improve engagement and efficiency. Likewise, Learning Content makes a significant contribution ($\beta = 0.301$, $p = 0.000$), aligning with previous research that emphasizes the role of quality content in the success of the e-learning adoption process.

Design and Presentation have a significantly positive impact with a smaller effect size ($\beta = 0.061$, $p = 0.015$), implying that the mode of content delivery, both visually and structurally, remains essential to user experience, although less so than content personalization and quality. The Learning Assessment provision has shown a weak but significant impact ($\beta = 0.058$, $p = 0.014$), underlining that the assessment mechanisms within these environments contribute to the overall learning effectiveness, though this impact is still emerging. Adaptation and Personalization shows a significant positive effect ($\beta = 0.345$, $p=0.000$), signifying the importance of this aspect in enhancing the efficacy of adaptive learning environments through data insights and information processing. Moreover, Institutional Ethics and Governance decrease ($\beta = 0.240$, $p = 0.000$), underscores the importance of ethical frameworks, security measures, and regulatory compliance to achieve trusted and sustainable digital education ecosystems.

The extraordinarily high R^2 value (0.988) of the model for the dependent construct implies that the independent variables account for about 98.8% of the variance in adoption and effectiveness. That implies extraordinarily strong explanatory power, further corroborating the model's robustness. Therefore, the controls with the structural model give us a validation point of how we are hypothesizing works together and signs significance. Overall, the high R^2 value and the significant path coefficients confirm the robustness of this model, pointing to the importance of personalization, content quality, and institutional governance in the successful deployment of AI-enabled adaptive e-learning systems.

Owing to the exceptionally high coefficient of determination ($R^2 = 0.988$), concerns regarding standard method variance (CMV) received particular attention. In addition to procedural remedies such as respondent anonymity and randomizing item order, the Harman single-factor test was also used, showing that a single unrotated factor accounted for 29.4% of the variance, which is considerably less than the critical 50% threshold. Further, the non-significant effect sizes from a standard latent factor test in the CFA argued against significant inflation of structural relationships due to CMV.

The next step in confirming the structural model was calculating the path coefficients to test the hypothesized relationships between independent variables and the endogenous construct: Adoption and Effectiveness of AI-enabled Adaptive E-Learning Systems. The analysis gives the original sample values, and thus the t-statistics and p-values and allows you to know whether each path was substantial. A statistically significant path has a p-value of 1 of .96 at 95% confidence level. The direct effects results for each hypothesized path of the model, standard error measures, and significance levels of each path are presented in table 5 below.

Table 5: Path Testing.

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (IO/STDEVI)	P Values
Direct Effect					
Adaptation and_Personalization -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.345	0.346	0.029	11.957	0.000
Data Processing using Learning Analytics and AI -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.512	0.508	0.039	13.099	0.000
Design and Presentation -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.061	0.058	0.025	2.422	0.015
Institutional Ethics_and Governance -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.240	0.239	0.042	5.732	0.000
Learning Assessment -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.058	-0.053	0.024	2.457	0.014
Learning Content -> Adoption and Effectiveness _of AI-enabled Adaptive_E-Learning Systems	0.301	0.302	0.029	10.411	0.000

The results shown in Table 5 confirm that all six direct paths are statistically significant, as all p-values are less than 0.05 and t-statistics exceed the critical threshold of 1.96. This provides strong empirical support for the proposed hypotheses. The most influential predictor is Data Processing using Learning Analytics and AI, with a path coefficient of 0.512 ($p = 0.000$). This indicates a strong and statistically significant relationship between adoption and effectiveness. This finding highlights the central role of data-driven decision-making and analytics in enhancing adaptive e-learning environments. Adaptation and Personalization also demonstrate a notable impact ($\beta = 0.345$, $p = 0.000$), emphasizing the importance of customizing learning experiences based on individual learner profiles. Learning Content contributes meaningfully to the model ($\beta = 0.301$, $p = 0.000$), reinforcing the idea that the quality and relevance of content are essential for successfully implementing AI-enabled e-learning systems. Although Design and Presentation has a relatively lower path coefficient ($\beta = 0.061$, $p = 0.015$), it remains statistically significant. This suggests that the interface and visual appeal, while less critical than other constructs, still influence user adoption. Institutional Ethics and Governance ($\beta = 0.240$, $p = 0.000$) also play an essential role, underlining the necessity of ethical considerations, policies, and organizational leadership in supporting digital transformation in education. Finally, Learning Assessment shows the most minor yet still significant impact ($\beta = 0.058$, $p = 0.014$), indicating that the role of adaptive assessments should not be overlooked, even if its effect is more modest.

5. Discussion

Using Palestine as a case study, this study investigated the critical factors that encourage the adoption and effectiveness of AI-enabled adaptive e-learning systems (AI AELS) in educational environments challenged by conflict. Based on the data collected from 207 valid survey responses and framed around six key constructs, this study presents key findings on how adaptive technologies may be more appropriate and deployed within fragile and resource-constrained contexts. Data Processing using Learning Analytics and AI ($\beta = 0.512$, $p < 0.001$) was the best predictor of system adoption among the six hypothesized domains. One significant implication is real-time, AI-driven analytics' central role in personalizing learning pathways, tracking student performance, and informing pedagogical choices. The outcome is consistent with the doctrine of Long and Siemens (2011). It confirms recent work by scholars, which described how strong analytics systems (mainly when processed locally) promote uptake by enhancing system utility and safeguarding learner privacy. Adaptation and Personalization AI also had a robust and statistically significant effect ($\beta = 0.345$, $p < 0.001$) supporting the widespread belief that personalized learning environments enhance the engagement, satisfaction, and motivation of learners (Essa et al., 2023; Kabudi et al., 2021). Adaptive systems that can adapt to variable patterns of attendance and trauma-induced learning challenges are crucial in conflict-affected environments where learning is often interrupted.

The Impact of Learning Content on Adoption: Learning Content had a significant and positive influence on adoption ($\beta = 0.301$, $p < 0.001$), confirming that instructional materials' quality, relevance, and inclusiveness play a critical role in shaping user acceptance. This observation corresponds with the results in prior literature, especially relevant in Palestine, where integrated systems using culturally adapted content in line with national curricula have demonstrated significantly higher engagement (Halkiopoulos & Gkintoni, 2024). This study also found that Institutional ethics and governance ($\beta = 0.240$, $p < 0.001$) were also significant ($p < 0.05$), emphasizing trust, transparency, and ethical oversight in implementing AI-based educational tools. As noted by Nguyen et al. (2023) , ethical implications regarding data protection, IP compliance, and institutional accountability are further compounded in conflict zones, where digital surveillance and fragmentation of governance are endemic risks.

While Design and Presentation AI ($\beta = 0.061$, $p < 0.05$) also adds to similar but more modest statistically significant effects, it improves usability, interface satisfaction, and ultimately adoption, hence its inclusion in the model. This aligns with trauma-informed, low-bandwidth, and culturally sensitive design principles articulated by Al-Azawei et al. (2016) and taken up in the Tech for Palestine Initiative, which can improve learners' experience. However, their influence on adoption may be less prominent than other constructs. The Learning Assessment AI had the least potent effect on the use of mathematics compared to all other model variables but was still statistically significant ($\beta = 0.058$, $p < 0.05$). Their body of work does indicate a possible limitation in existing assessment tools, which have yet to be fully attuned to the realities of trauma, infrastructural instability, and learning that takes place asynchronously. A prior study asserts that classic models for assessment may need to be advanced for measurement in conflict environments, at least, unless intentionally modified for asymmetric cognitive performance and in addition to non-network-enabled capabilities. Thus, systems developed for politically stable resource-rich contexts require a radical redesign to accommodate learners in learning contexts' infrastructural and psychological realities.

The discovery that Data Processing ($\beta = 0.512$) had an even greater weight compared to Institutional Ethics & Governance ($\beta = 0.401$) in driving AI-AELS adoption led one to suggest that in settings with conflict-affected schoolteachers, they could attach more value to the practicality of AI tools rather than ethical compliance. This could be underpinned by chronic resource constraints, where the need for data-driven decision-making & analytics, and personalization can feel more urgent than long-term governance mechanisms. In other words, if the learning data bottleneck can be addressed by processing and interpreting this data quickly, a concrete solution to long-term pedagogical and administrative challenges may take precedence over vague ethical considerations. On the other hand, the effect of Learning Assessment ($\beta = 0.058$) is reasonably small because of two reasons that may interact with each other. To begin with, adaptive AI-driven assessments are unknown in Gaza owing to the lack of experience with earlier formative analytics systems among local teachers. Another possibility is that there are structural misalignments between AI-based continuous assessment models and the existing summative, high-stakes examination culture in the region. This distance might reduce perception of relevance and utility, thereby reducing its role in adoption intentions. These findings will (hopefully) expedite capacity-building efforts and assessment models that are culturally-informed and pedagogically oriented to ensure empirically sound but also educationally useable AI-based evaluation tools.

5.1. Limitations of the Study

Several limitations must be acknowledged. Firstly, the research employed a cross-sectional design, capturing relationships at a single point in time; therefore, causal inferences between the identified factors and AI-AELS adoption cannot be definitively established. Longitudinal studies are needed to explore these dynamics over time and provide stronger evidence of causation.

Secondly, the participants evaluated hypothetical scenarios rather than directly experienced AI systems due to limited real-world implementation in Gaza. This reliance on hypothetical evaluations may introduce perception bias, as participants' responses reflect anticipated rather than actual interactions with the technology.

Thirdly, the data were collected using self-reported measures from teachers and ICT coordinators, potentially subjecting responses to social desirability or subjective bias, despite assurances of anonymity. This limitation could affect the accuracy of responses related to sensitive issues, such as ethical considerations or perceived system effectiveness.

Fourthly, a convenience and institutionally facilitated sampling strategy was employed due to practical constraints related to conflict and limited access to schools in Gaza. While necessary, this approach may limit the generalizability of the findings to all schools in Palestine or other similar conflict zones.

Fifthly, the exceptionally high R^2 value (0.988), although indicating strong model fit, might suggest potential common method bias due to single-source data collection for both predictor and outcome variables. Procedural remedies were used to mitigate this bias, but future research could benefit significantly from employing multi-source data collection or objective measures of actual system use.

Finally, while this study offers a nuanced and context-sensitive perspective from Palestinian schools, the unique socio-political, infrastructural, and educational challenges of Gaza imply that findings may not be directly transferable to other conflict-affected or fragile regions without additional contextual adaptation and validation. To address these limitations comprehensively, future studies could adopt longitudinal research designs, multi-source data collection, and field-based experiments or pilot implementations to provide deeper insights into causal mechanisms and practical applicability of AI-enabled adaptive e-learning systems in conflict-affected environments.

6. Conclusion

In summary, this study found that:

- Data Processing using Learning Analytics and AI and Adaptation and Personalization AI were the strongest predictors influencing AI-AELS adoption.
- Learning Content quality and Institutional Ethics & Governance also significantly influenced adoption.
- Design and Presentation AI and Learning Assessment AI, while statistically significant, showed comparatively smaller impacts.

These findings underscore the importance of prioritizing context-specific, ethically robust, and adaptive design features in developing AI-enhanced educational systems for conflict-affected areas like Palestine.

This study is a stark reminder of the need for an applied, context-sensitive approach that reconciles technological promise with sensitivities in fragile settings. To respond to this need, a policy formulation roadmap needs to be drawn, custom-made for the understanding of policymakers, NGOs, and educational authorities. Step one is aligning the infrastructure; we need AI solutions that work well on low-spec devices and with intermittent connectivity (as most schools cannot afford more), so they can leverage existing school hardware/bandwidth configurations. It is equally essential to create a trauma-informed design and incorporate a psychosocial lens into the delivery of AI content to ensure that certain features do not cause traumatization and instead create spaces for healing and learning. Building the capacity is another pillar, which means having ongoing teacher training that combines technical skills for the integration track, as well as pedagogical strategies for developing training models that work effectively with AI tools in classrooms and schools. Thus, it will be critical to integrate ethics and governance explicitly into the development of lightweight but enforceable ethical guidelines that are uniquely suited to conflict-zone realities, with due regard both to practical utility and safeguards against misuse. While this framework was generated in the context of Gaza, its underlying principles can be adapted to other fragile environments (e.g., Syria, Yemen). When they do, adaptations (to things like curriculum particulars, language and cultural sensitivities, and governance capacity) need to be built into the design and deployment process. This flexibility ensures that AI-enabled education systems are location, context, and operations-agnostic, addressing a wide range of conflict-affected areas.

This work adds to the burgeoning literature on integrated teaching in AI education, providing an empirical and conflict-sensitive perspective on scaling agent-based adaptive e-learning systems. The research is limited to six interrelated domains, Institutional Ethics & Governance, Learning Assessment, Design & Presentation, Adaptation & Personalization, Data Processing with AI, and Learning Content, to develop a multifaceted clue to what incentivizes adoption in fragile educational contexts. It appears that the provision of those enablers that align best with enhanced technical adaptability, ethical trust, and learner-centered personalization are the most powerful in ensuring adoption. It questions the assumption that one-size-fits-all, high-tech solutions are enough on their own. Instead, it calls for a localized, resilient, and ethically grounded approach to AI integration in education that recognizes the lived realities of learners experienced in occupation, displacement, or economic hardship. For policymakers, education leaders, and AI developers, these findings highlight that a lot can be learned from designing systems with local stakeholders that invest in decentralized governance models and trauma-informed, low-tech-compatible solutions. As AI takes on an increasingly important role in the future of education, its deployment must be inclusive, equitable, and conflict-sensitive.

6.1. Ethical Approval

Data Availability Statement: Data are available on request from the corresponding author. The Ethical Committee of the UKM University, Malaysia has granted approval for this study.

6.2. Acknowledgements

The authors confirm that this manuscript is original. An AI-based tool was used only for language editing (grammar/clarity). All ideas, data, analyses, and conclusions are entirely the authors' own.

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