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AI-Enabled Adaptive E-Learning Systems Adoption in Conflict Zone: Case Study of Palestinian Schools

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Abstract **– Transforming education in conflict zones has not been extensively studied. This paper aims to investigate higher educational levels in conflict zones for Artificial Intelligence (AI)-enabled adaptive e-learning systems concerning schooling in Palestine. This paper constructs a comprehensive technology adoption model that explains these factors in distance education without needing the Internet. The descriptive-analytical method and the questionnaire were used for data collection. The survey included 30 questions adapted from previous studies. The focus was on the conflict areas before the war on Gaza. An electronically designed questionnaire was distributed. Data from 205 schools in Gaza were analyzed using Smart PLS 4. The results show that Perceived Usefulness (PU), Perceived Ease of Use (PEU), and System Quality (SQ) positively influence BI Behavioral Intention toward system use, while IQ Information Quality indicates areas for improvement. This paper shows AI-powered e-learning systems' transformational impact in bringing customizable, convenient, and scalable learning in resource-constrained regions.**

The findings suggest the importance of Information and Communication Technology (ICT) infrastructure, digital literacy training, and inclusive strategies to provide equitable access to these technologies in conflict zones and inspire others.

Keywords **– AI-enabled adaptive e-learning, distance learning, ICT infrastructure, DeLone and McLean IS Success Model, educational technology adoption.**

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1. Introduction

In recent years, significant changes have occurred in the field of educationincluding AI field. However, one remarkable innovation is AI-driven adaptive e-learning systems that significantly render the educational process more productive and beneficial for students [1]. It uses AI algorithms to customize the academic content and experiences according to each student's need, preference, or progress, leading them to a personalized learning environment. On the other hand, using these sophisticated e-learning systems is not an easy deal for warzones. Cooperation is already tricky in conflict zones due to unstable locations, disruption, and lack of facilities for conventional education. AI-enabled adaptive e-learn systems can be a good solution to such scenarios in the scale, flexibility, and accessibility aspects of schooling, as AI enables adaptation features, which is an inherent need amidst turbulence. Moreover, conventional educational practices worldwide have been affected by rapid progress in information, multimedia technology, and communication technology [2].

One of the primary developments that followed this surge was through AI-driven adaptive e-learning platforms. Artificial intelligence allows these systems to provide a more personalized learning experience conducive to every student's requirements and pacing [3]. AI-based adaptive learning, in operational usage, refers to educational technology that uses AI algorithms for learning and customization of the student experience based on individual performance and preferences [3].

E-learning has emerged as an effective learning method with many benefits, including facilitating maximum flexibility and providing full scalability and personalized learning experiences [4]. Their goal is to teach students not by providing the same content to everyone but by tailoring the learning experience to each student's unique needs, helping them achieve personal growth, mastery, and even leaving a legacy [6]. These systems can identify personalized learning requirements and determine the most effective delivery methods [5], [44]. It is essential to evaluate these advancements in the context of their potential applications and perceptions of e-learning, particularly in developing regions such as Palestinian schools.

This may include the lack of appropriate infrastructure, socio-political instability, and economic limitations [4], [45]. Artificial intelligence adaptive learning systems may help solve some of these problems by providing students with scalable, flexible, and individualized opportunities. This is especially important in places like Gaza Strip, where conflicts often interrupt traditional education methods. However, this paper focuses on the drivers of accepting and adopting AI-enabled adaptive e-learning systems in conflict zones, with the Gaza Strip as the case study.

Educational innovation is vital to societal advancement despite a thriving tech scene across Palestine and its diaspora [7], [8]. However, this paper is organized into seven sections. The introduction presents the progress made in ICT (Information and Communication Technology) and AI-based adaptive e-learning systems, underscoring their potential to transform education delivery - particularly within conflict zones like Gaza Strip, an exceptional case with its difficulties. The review addresses the research on e-learning, adaptive systems as intelligent entities, and the advantages/ disadvantages of using intelligent entities in real-life scenarios, followed by an Extending Technology Acceptance Model (ETAM) adopted for Adaptive Educational Hypermedia Systems.

2. Literature Review

Education in conflict zones faces a complex landscape of additional and unprecedented obstacles, including instability, lack of resources, or professionally trained teachers.

Additionally it often disrupts the traditional methods of education. In recent years, however, technological innovations - especially in AI- have emerged as a ray of hope in the face of these challenges. AI-enabled adaptive e-learning systems have emerged as exceptionally potent technologies offering tailored education delivery in flexible and personalized environments.

This empowers systems to leverage sophisticated algorithms, tailoring educational content for individuals and enhancing engagement and effectiveness. However, implementing AI-powered e-learning in conflict zones comes with its challenges. For example, [9] provided a comparative study focusing on Saudi Arabia based on e-learning and in-person education. The study data indicate that e-learning, when implemented correctly, shows an effectiveness equivalent to other methods without being superior or inferior to them. This further proves the possibility of using e-learning to encourage learning integrity and accomplish educational aspirations in resource-challenged settings. Moreover, [10] indicates that e-learning could overcome these obstacles and provide education to women who face economic, security, or socio-cultural constraints, regardless of the high system’s performance. E-learning may be a solution that can facilitate gender equity in an educational system, especially for those who live in conflict zone areas, by providing flexible and accessible learning opportunities that transcend the constraints of traditional settings. [11] suggestes that the e-learning functionalities, especially in conflict areas like the Central African Republic, could be extended using ZeroConf protocols. Using different VPN modes and TVWS transmission channels, showed how remotely-separated teachers and students can remain connected in real-time parallel to in-person meetings. This ensures continuity in education and sustainable future for youth by providing them with educational opportunities, thereby reducing the appeal of armed groups.

[12] underlines the impact of the Syrian conflict on access to higher education, significantly impacting health professions training and provision. Health professionals and educational institutions have been directly targeted, leading to a more significant shortage of doctors. The IIHE (Institute of International Health and Education) Online Education for Displaced Syrian Medical Students (OEDSS) was a response to these challenges. To date, the OEDSS program has educated 525 students. The program enables smartphones, the computer of choice in these remote locations, to access lectures. This indicates that, instead of depleting the limited electricity available by the end of each school day, students can download course materials during class (potentially using additional phone power for this purpose) and still preserve several hours of battery life until evening. In addition, [13] highlightes the significant destruction of educational infrastructure and consequential issues followed by a lack of traditional education. [13] recommendes e-learning as a possible solution for problems such as financial, security, and administrative constraints by allowing course continuity to carry on through this crisis, such as those caused by bushfires.

However, [13] highlighte that investing in ICT infrastructure to support e-learning can significantly enhance educational outcomes during recovery. In addition, [14] argued that Information and Communication Technology (ICT)- ICT-based educational systems can help improve the quality and accessibility of higher education compared to the conventional system, and improved access to information technology will lead to long-term stability.

Student learning and educational outcomes have garnered increased interest as systems-level obstacles to academic success pose limitations in some geographic regions. Showing this relationship with Palestine, [49] highlighte the possibility of transformation by incorporating information systems in education. As [49] illustrate, as highlighted in [49], education is a cornerstone for empowering individual capabilities, advancing social equity and driving sustainable economic development. Indeed, the integration of technology and information systems is vital in conflict-affected areas such as Palestine, where educational infrastructures are often marked with disruption. This study aims to provide a bibliometric analysis of education-related academic publications in Palestine extracted from the Web of Science (WoS) database. The study applies keyword analysis to "Palestine" and "education" to produce relevant insights into the research stream regarding information systems in education. From analytical methods like the co-author, keyword, and bibliographic coupling, it is easy to see the collaborative networks and thematic blocks in this area using programs like Vos-viewer. These analyses show that scholarly energies are converging on the idea that technology can help surmount hurdles to learning. One interesting feature of Seren's study is the consideration of the relationship between information system emphasis and student outcomes, as measured by PISA mathematics performance. This bivariate analysis finds a strong positive correlation between both factors–countries that emphasize establishing educational information systems in the early stages of development also demonstrate a tendency to achieve superior outcomes in international assessments. The announcement reflects the strategic role of technology in improving learning outcomes where resources are lacking or conditions are unstable (politically or socially). This research highlights the economic impact of the developing role of information systems in education. [49] demand for increased investment in educational technology bridges existing gaps to take Palestine to a level of quality that matches higher levels in education and economic performance by providing a menu of options that address specific rights.

With the broader discussions on effective ICT structure and literacy, especially in the context of AI-enabled adaptive e-learning systems, 79 of the findings align. Thus, integrating information systems in Palestinian schools might be one of the best ways to respond to socio-political problems, enhance education quality, and contribute to long-term economic sustainability. The works of [49] indicate that theoretical models such as TAM (Technology Acceptance Model) , DeLone and McLean IS Success Model are relevant to a deeper understanding of technology's role in socio-economic development, as mentioned by Seren [49], allowing the exploration of areas where emergent trends can address fundamental materials issues.Such questions have important empirical implications for forming patterns that deeply shape society. As discussed above, these models can also help frame educational information systems' adoption and effectiveness, providing valuable insights for policymakers and educational practitioners seeking to spur innovation in conflict-affected areas.

[15] stresses the importance of investing in resources, training, and infrastructure required to maintain such AI-driven systems, ultimately leading towards strategies on overcoming these obstacles as best to harness the potential benefits of utilizing AI for education. [16] reveales that AI algorithms, such as Decision Trees and Artificial Neural Networks, effectively improve learning adaptation. The joint use and combination are important, e.g., in dataset mining and learning experiments on platforms like Moodle. [17] studies the scenario that could not have been altered given unforeseeable events such as (COVID-19, since no one had drilled into details 'details' merci commerce action to request, then AI gears up momentarily from E-Commerce dynamics during crises. [17] highlights the advantages of personalized learning, immediate feedback, and hands-on experience. With the help of AI-powered algorithms and IoT-enabled devices, even student engagement can be monitored to improve learning experiences instantly. The authors note that ethical and equitable usage of these technologies is paramount to fair access to all students. [18] reveales that educational institutions provide reference numbers rather than authors could solve these moral dilemmas if they want to employ AI-assisted technologies to make the learning process efficient and ethical. However, the literature points to the vast transformative possibilities offered by AI-enabled adaptive e-learning systems in conflict zones. They articulate how e-learning can deliver universal, quality education even in turbulent times; advance gender equality and empowerment of women (SDG 5); foster fraternity between nations or better - continental integration as well as socio-cultural development and action against poverty - local resilience.

However, the humanitarian and development application of these technologies in conflict zones require ethical reflection and large investments in ICT infrastructure to be fully harnessed.

Improvement in ICT has been a sign of development similar to the improvement of educational technology that boiled down from customary models into digitized form, affecting input on pedagogical designs. This transformation began to be made possible by the internet in the late 1980s and is now evidenced, despite all its disruptive potential, nowhere more effectively reminded the many, which means in terms of access: places like Palestine; Moodle as an e-learning platform. In other words, e-learning can only be effective if the technological infrastructure is available and if users are open to technology (adopters); furthermore, they must have an acceptable level of digital literacy, which enables them to use equipment satisfactorily. The ASOT theoretical framework formulated has resulted in the proliferation of models like ISSM (Information System Success Model), TAM (Technology Acceptance Model), etc., within academia [2], [3], [4]. Itis noted that theories analysis implementations according to non-functional terms are not enough for assessing implementation success. According to the TAM developed by Davis in 1989, its primary premise states that when users perceive technology as useful and easy to use, this will reflect on their attitude toward the potential adoption of such technologies [19]. This model has been widely used in technology adoption research, like e-learning platforms [20], [21]. This model (ETAM) has been further refined to include other constructs i.e., result demonstrability, job relevance, subjective norm, image, output quality, and perceived risk [22], [23], 24]. The relevance of TAM and its extensions in the context of AI-enabled adaptive e-learning systems, specifically in developing countries, has not yet been fully explored [25], [26]. In this context, it should be noted that Palestine is a developing country and, these days, is considered as a conflict zone.

Furthermore, DeLone and McLean's IS Success Model, originally proposed in 1992, considers the significance of system quality (SQ) and information quality (IQ) for user satisfaction as well as usage [23]. More recent work has sought to understand complex dynamics between factors, such as user engagement or cost-benefit analysis, with a particular focus on AI-enabled educational software [27], [28], [29]. Though the factors influencing the adoption and use of e-learning have been widely discussed in past research, such as technological barriers, individual-to-use technologies, and other organizational-level variables [30]. The literature still lacks which explores AI-enabled adaptive e-learning systems specifically focusing on conflict [34], [35], [36].

This paper aims to fill this gap by integrating and extending well-known theoretical models (e.g., TAM, DeLone & McLean IS Success Model) with unique contextual factors specific to the Palestinian educational domain [28], [29], [30], [33]. More specifically, it studies how the introduction of AI-powered functionalities such as personalized learning paths, intelligent feedback, or adaptive content delivery may impact perceived ease of use and usefulness (in line with TAM), which in return influences intention to actual use (according to UTAUT2 model) electronic leaning system adoption amongst Palestinian educators and students [8], [25], [27], [31].

In addition to shedding light on these dynamics, offering an original contribution supplies the basis for a more advisable design and deployment of AI-powered e-learning interventions in LMICs [30], [23], [24], [26], [37]. However, this paper uses a theoretical framework (ETAM and the DeLone & McLean Information Systems Success Model) to explain most of the adoption of e-learning in conflict zones. Context-specific factors, such as socio-political challenges and technological constraints, are critical in the adoption of e-learning systems within conflict zones and are integrated into this framework. Thus, the next section explains the development of the study hypothesis and conceptual framework.

3. Hypothesis Development

In conflict settings such as Palestine, the adoption and use of an AI-enabled adaptive e-learning system may be influenced by several factors, including the quality of the system itself (system quality), the design of the User Interface (UI) to facilitate effective communication of critical information (UUDI), and the availability of innovative services such as digital learning software along with supportive tutorial content and related materials shared with users. These attitudes and beliefs are crucial in shaping user perceptions of these technologies, ultimately determining their success or failure in battlefield deployment.

The perceived ease of use can be significantly impacted by the quality or level of sophistication reflected in a device's UI, which is specifically related to UI Quality here. An intuitive and well-designed UI can reduce cognitive load, making it easier for users to interact with the system. Well-designed UI improves usability and user satisfaction, which is crucial for technology acceptance [37]. Research shows that a user-friendly interface is essential for facilitating technology usage among users, which will improve their overall experience and the chances of re-engagement. In addition, system quality includes reliability, performance, and functionality.

In addition to reliability, performance, and functionality, the user interface (UI) quality significantly enhances the perceived ease of use. A system with smoother operation and higher reliability is consistently perceived as easier to use [12]. Many studies have found that system quality significantly affects user satisfaction and perceived ease of use, such aspowerful systems with few technical failures will drive better experiences [12], [16].

Perceived usefulness is highly affected by the quality of information, expressed as one characteristic (quality) that explains accuracy, pertinency, and extensiveness based on responses received from end users of systems. Better system perception can be achieved by improving the information engaged by user-oriented high systems [38]. This is important for the adaptivity of e-learning systems since they must promptly respond by providing relevant content. The best way to do this is by developing a user-generated system where users receive all the necessary information, which acts as an internal data measurement, ensuring that every piece of content fulfills the educational and practical aspects of their learning process. However, system quality significantly impacts ease of use and perceived usefulness [3]. Users are more likely to perceive the benefits of a system as better if the high quality is reliable and provides effective functionalities. This aligns with the IS Success Model, which suggests that system quality will influence perceived usefulness and overall satisfaction [12]. As the system is perceived as more reliable and efficient by the users to appreciate its utility, preference also results in an increased willingness to use it.

Perceived ease of use is another central construct influencing the behavioural intention to adopt specific technologies. As per the TAM, users should feel the system is intuitive and easy to interact with, as emphasized in this concept. While the idea may seem straightforward in theory, its practical execution proves to be significantly more challenging. If users think technology is easy to use, the cognitive and technical barriers are nondemanding, and they are willing to use the system quickly [13]. The literature contains extensive documentation of a relationship between perceived ease of use and behavioural intention, meaning that easier-to-use systems are more likely to lead toward continued and repeated usage. The simple interface and the ease at which users can accomplish their tasks play a significant role in how users perceive the utility and usability of the system. Thus, creating user-centric systems focusing on usability is pivotal to increasing uptake and ongoing use. Moreover, perceived ease of use plays a dual role in promoting initial acceptance and impacting users' long-term satisfaction and loyalty, suppose that a technology prevents errors and minimizes the effort required to learn and operate a system.

In that case, users will view technology as a valuable tool in achieving the goals they were initially implemented, increasing the likelihood of continued use. This underscores the need to understand user experience in manners that violate recent technologies, ensuring that technological solutions and delivery methods align with concepts that users find familiar and in sync with their intuitive experiences [13].

Numerous computer adoption studies have widely substantiated this relationship, showing that more usable interfaces reduce barriers to entry and increase the time training users spend interacting with it. Another important determinant of behavioural intentions is perceived usefulness and the extent to which users believe using the system will improve their performance. Systems perceived as being useful will be used continuously [1]. This is particularly evident in educational environments, where the reliability of a system directly impacts learning outcomes. When users realize that the system contributes significantly to their learning, they are more motivated to use it. Finally, the existing literature establishes a clear and well-documented relationship between behavioural intentions and the actual use of a system [22].

Positive intentions to use a system often lead to actual usage behaviour [43]. This relationship is consistent in the technology acceptance literature, with users with a behavioural intention often following through and integrating it into their daily routine [4]. These hypotheses are collectively designed to probe the effects of system quality, UI, information quality, Perceived Ease of Use (PEU), Perceived Usefulness (PU), and behavioural intentions in adopting and utilizing AI-enabled adaptive e-learning systems in war zones. This study investigates how these factors are interrelated and thus contributes more competently towards successful implementing of e-learning technologies in the most challenging environments. Therefore, this paper proposes a hypothesized relationship between behavioural intentions and the actual use of the system. However, Figure 1 shows all factor and their interplay deduced from the literature.

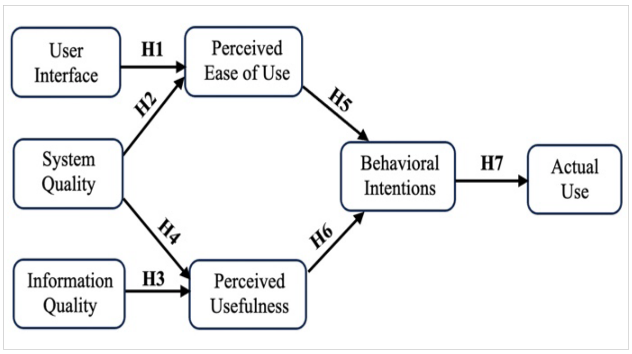

Figure 1. Theoretical research framework

This study approaches its theoretical background from the perspective of a synthesis of the Extended Technology Acceptance Model (ETAM) and the DeLone and McLean Information System Success Model [28]. This integration indicates an intention to embrace a holistic approach to understand the dynamic between users and technology, acknowledging the importance of technical and human factors involved in the interaction. In this model, essential factors, including UI, PEU, and PU, help to explain the interaction and perception of the system experienced by an individual. The UI, for example, is a threshold that users cross when interacting with the technology and directly impacts their perceptions of ease of use, bonds of functionality, etc. PEU and PU are key elements of ETAM [26], reflecting the cognitive and affective user responses, reinforcing the importance of appealing systems (easy to use), the perception that using a system is worthwhile and effortful, with the aim of achieving optimal results, serves as a key benchmark in evaluating the effectiveness of systems. Additionally, incorporating Information Quality (IQ) and System Quality (SQ) emphasize the technical aspects of system efficacy. Where IQ is about the quality, relevance, accuracy, and timeliness of the information provided, SQ speaks to the system's trust, performance, and usability. This is a necessary building block of trust and user satisfaction, an input to Behavioral Intentions (BI) and, ultimately, to Actual Use. BI indicates willingness to use the system, which precedes its actual use. So basically, by creating a model using these different components, user perceptions and the system's characteristics can be linked to outcomes success or failure. This comprehensive perspective aligns with earlier literature and provides a framework for system design, development, an implementation to help support user engagement, and satisfaction with health information dashboards.

4. Methodology

This paper used a quantitative approach and a deductive design. However, this paper was designed to investigate AI-enabled adaptive e-learning system adoption in conflict zones, seeking to overcome any potential barriers within these regions hindering education delivery. The investigation is vital because education in conflict areas is a fundamental human right and is integral to peace, stability, and development. These e-learning systems can account for the changing circumstances of learners at any moment, continuously provide education even in times of disruption, and cater to a variety of learning needs - all with the help of AI, both contributing extensively towards individual and community resilience.

The survey comprises eight sections: information quality, system quality, demographic details, user interface design, perceived usefulness, ease of use, behavioural intentions, and actual use. It included 30 questions adapted from existing studies [7], [38], [19], [28]. Seven field experts reviewed these questions over three rounds, endorsing 25 for the final survey. However, Table 1 below provides questionnaire items used in this paper. A preliminary test with 46 teachers assessed the survey's validity, achieving a Cronbach's alpha value of 0.906, indicating high reliability [30].

Table 1. The construct and measurement items

Construct	Item	Measurements
System Quality	SYS1	It is easy to use the services and functionalities of the AI-enabled adaptive learning system.
	SYS2	The interaction with AI-enabled adaptive learning system is quite flexible.
	SYS3	The adaptive learning system powered by AI is robust.
	SYS4	The system's response time is satisfactory.
Information Quality	IQ1	I find the AI-powered adaptive learning system relevant for my needs.
	IQ2	This AI-enabled adaptive learning system provides exactly the right amount of knowledge at the right time.
	IQ3	AI-Personalized Learning System Up-To-Date Information and Content
	IQ4	The adaptive learning system powered by AI is proven to be accurate.
Perceived Usefulness	PU1	My academic productivity is higher, thanks to the AI-enabled adaptive learning system.
	PU2	It keeps me at my top performance in my academics with its AI-enabled adaptive learning system.
	PU3	The AI smart adaptive learning system simplifies teaching in distance learning.
Perceived Ease of Use	PEU1	I can also teach asynchronously using an AI-enabled adaptive learning system.
	PEU2	The AI-enabled adaptive learning system is user-friendly.
	PEU3	Learning to operate the AI-enabled adaptive learning system is easy for me.
User Interface	UI1	Different features are integrated with the AI-enabled adaptive learning system.
	UI2	My opinion of the AI-enabled adaptive learning system depends on the user interface.
	UI3	The Integrated Artificial Intelligence Adaptive Learning system allows for quick learning usability due to its enriched user-friendly interface.
	UI4	Correspondence with the AI-enabled adaptive learning system through the user interface
Behavioral Intentions	BI1	So, I am not influenced to use the AI-powered adaptive learning system.
	BI2	They may want to utilize the AI-enabled adaptive learning system
	BI3	I would like to use the AI-enabled adaptive learning system for the entire year.
	BI4	The AI-enabled adaptive learning system makes learning more fun.
Actual Use	AU1	The AI-enabled adaptive learning system helps everyone learn more.
	AU2	I do use the AI-assisted adaptive learning system often.
	AU3	The AI-based adaptive learning system is a daily feature of how I teach.

The questionnaire is organized into two sections. The first section consists of the respondents' demographic information, and the second section provides questionnaire items to measure the study variables, as shown in Table 1 above. However, demographic questions covered school geographical location, student gender, operational timeframe, educational level, and governance. A 5-point Likert scale measured all latent variables, with responses ranging from 1 to 5. The survey took approximately 15-20 minutes to complete. The study engaged schools across Gaza Strip, chosen for its unique socio-political and educational landscape [8]. Public schools, government-run institutions, and UNRWA-managed schools were included to help inform educational policy and plans for technology implementation in similarly complex contexts. However, convenience sampling was used as the survey was available from July to September 2023. Gaza's Ministry of Education even sent an official letter encouraging government schools to participate, while groups facilitated distribution in UNRWA schools. Thus, responses were collected from 213 schools, reduced to 205 after eliminating duplicates. With 257 UNRWA and 421 government schools in Gaza, the sample size provides a solid basis for generalizing technology acceptance in the region [39]. However, the gender distribution of the schools showed a significant dichotomy, with male-only schools representing four-fifths of the sample (45.37%), whereas female-only were more than one-third, and mixed-gender formed barely over two-tenths remaining. This makes sense for a strong taste or demand for single-gender education in the schools in operation by morning, 67.80% of those that work at night and perform operations through networks of connections make up 3.20%. This strong preference for morning hours could be related to social norms, financial factors, or practical reasons. The growing prevalence of evening schools suggests a shift towards alternative education. This trend may be influenced by the needs of working adults or individuals who cannot participate in education during conventional business hours.

The distribution according to educational stages demonstrates that preparatory (46.34%) schools are the most common in case of 87 deadlines, followed by primary school (30.90%), then lower secondary and upper secondary level combinedly accounting for less proportion i.e., having an almost equal number at both levels amounting a total percentage around 22 [10]. This includes 29.27% of primary and secondary schools; The data shows that 75.61% of all schools are managed by the government and UNRWA manages some 24.39%, as indicated here:

This distribution reveals how states almost totally govern educational administration, while UNRWA functions as a somewhat but insignificant player. Geographically, the schools are distributed with 34.63% in Gaza followed by Khan Yunis at 24.39%, North Gaza representing a total of 14.15% while Rafah has contributed to roughly13.66%.

The analysis shows some patterns regarding the distribution and characteristics of the schools that were included in the study. The largest group consisted of male-only schools (93), followed by female-only schools (77) and a smaller number of mixed-gender schools (35). Predominantly, they also have single-gender education in the Middle East, which further illustrates the socio-cultural integration, especially in the region where only single-gender schools have been mostly preferred. Moreover, the morning was when most of the schools were functioning (139), and the evening had the smallest number of schools still running (66). Various practical considerations, including community culture, resources, and engagement levels, might drive this morning's schedule preference. When classified by educational stages, preparatory schools were the dominant category, with 95 institutions, followed by primary schools (60) and secondary schools (50). Such distribution signifies the predominance of middle-level educational institutes, thereby indicating a concentration on the basics and intermediate stages of learning. So, looking at management structures, 155 of the schools in the sample were run by the government, while the UNRWA managed 50. This highlights the importance of government regulation of education alongside international support through UNRWA. For geographical distribution, schools were distributed across the 5 main governorates in Palestine, including Gaza Governorate (71), Khan Yunis (50), North Gaza (29), Rafah (28), and the Central Region (27). This spatial distribution mirrors the socio-political and demographic context of the region, thus serving as a representative sample for this study. Smart PLS4 was utilized to assess the hypotheses using Structural Equation Modeling (SEM). SEM allows the analysis of quite complex relationships between several dependent and independent variables, taking mediating effects into consideration [32]. This method allowed in-depth scrutiny of the theoretical model, causing a better understanding of how the various factors interact and their effect on the outcome of education. The SEM analysis was performed to explore the relationships within the suggested model and its results are discussed in later parts of the paper to find out more about the forces and factors driving the use of AI-enabled adaptive e-learning systems in this specific context.

5. Results

This paper used Smart PLS4, as there are two important steps in order to reach the results of the study; the first is the measurement model and the structural model. The following sections explain the results of those tests.

5.1. Assessment of Measurement Model Assessment

The measurement model is used to assess the reliability and validity of constructs. This step helps ensure that the survey items measure what the theory intends. The measurement evaluation process involves evaluating the construct's weight of reliability, convergent validity, and discriminant validity using statistical indicators such as Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). These metrics assess each construct's internal consistency and discriminant validity before examining the structural model.

5.1.1. Reliability and Validity Testing

The model's reliability and validity were tested and were shown to produce satisfactory results, indicating good evidence for the strength of the constructs.

The Cronbach's alpha coefficients for all constructs, such as Actual Use, Behavioural Intentions, Information Quality, Perceived Usefulness, Perceived Ease of Use, System Quality, and User Interface, were above the widely accepted reliability threshold of 0.700.

This result shows that the internal consistency of the variables is acceptable according to the guidelines established in previous studies [47]. Finally, the composite reliability indices such as rho_c and rho_a also exceeded the threshold, confirming the model's reliability from multiple perspectives. Besides reliability, the evaluation of convergent validity offered additional support for the model's strength. All Average Variance Extracted (AVE) values of the constructs (between 0.587 for Perceived Ease of Use and 0.730 for Perceived Usefulness) exceeded the minimum criterion of 0.500. These values indicate that the constructs explain a high proportion of the variance of their respective items, indicating that the indicators are suitable for measuring their hypothetical constructs. The findings highlight the constructs' reliability in measurement, where high-reliability scores demonstrated by Cronbach's alpha statistics and satisfactory AVE values further affirmed their qualities of representing the constructs within the theoretical frameworks [45], [46]. The model's thresholds closely corresponded with those already established in the literature, supporting the model's plausibility and usefulness for examining the relationships between these variables in the study context [40], [41], [42], [43], [44]. See Table 2.

Table 2. Reliability and validity

Construct	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
Actual Use	0.709	0.823	0.610
Behavioural Intentions	0.831	0.889	0.668
Information Quality	0.794	0.866	0.617
Perceived Usefulness	0.813	0.890	0.730
Perceived Ease of Use	0.742	0.810	0.587
System Quality	0.776	0.856	0.598
User Interface	0.830	0.887	0.662

5.1.2. Discriminant reliability

Discriminant validity is tested and validated by the Fornell-Larcker criteria, Table 3. To understand how distinct a latent variable is from the other constructs [42], [44], [46]. In Table 4, the square root of AVE is indicated in bold on the diagonal Fornell-Criteria Larcker´s correlation matrix (Fornell-Larcker's criterion).

Only the remaining values indicate associations with other constructs. Discriminant validity is established by showing that the bolded value along the diagonal (square root of individual AVE) exceeds their corresponding inter-construct relationships. There is no exception; all the diagonal values are more significant than their non-diagonal counterparts. As a result, the discriminant validity of our framework is sound.

Table 3: Criterion of Fornell-Larcker

	Actual Use	Behavioural Intentions	Information Quality	Perceived Usefulness	Perceived Ease of Use	System Quality	User Interface
Actual Use							
Behavioural Intentions	0.833						
Information Quality	0.464	0.648					
Perceived Usefulness	0.489	0.711	0.379				
Perceived Ease of Use	0.080	0.077	0.054	0.015			
System Quality	0.405	0.588	0.300	0.435	0.116		
User Interface	0.564	0.797	0.431	0.485	0.005	0.326	

The Heterotrait-Monotrait (HTMT) ratio is also found to be a better test for checking the reliability of discriminator.

All the HTMT ratios are lesser than 0.9 (Table 4), this indicates good discriminant's reliability, refers to [48].

Table 4: R-square and R-square adjusted

Variables	R-square	R-square adjusted
Actual Use	0.480	0.478
Behavioural Intentions	0.351	0.345
Perceived Usefulness	0.257	0.249
Perceived Ease of Use	0.016	0.006

5.1.3. Factor Loadings

The latent variable types and their constituent factor loadings are displayed in Figure 2 below. Their factor loadings indicate the degree to which different items contribute to a given construct.

The factor loading should be greater than 0.700 for the application to considered.

The positive factor loading for each indication of a one off and build has a positive factor loading.

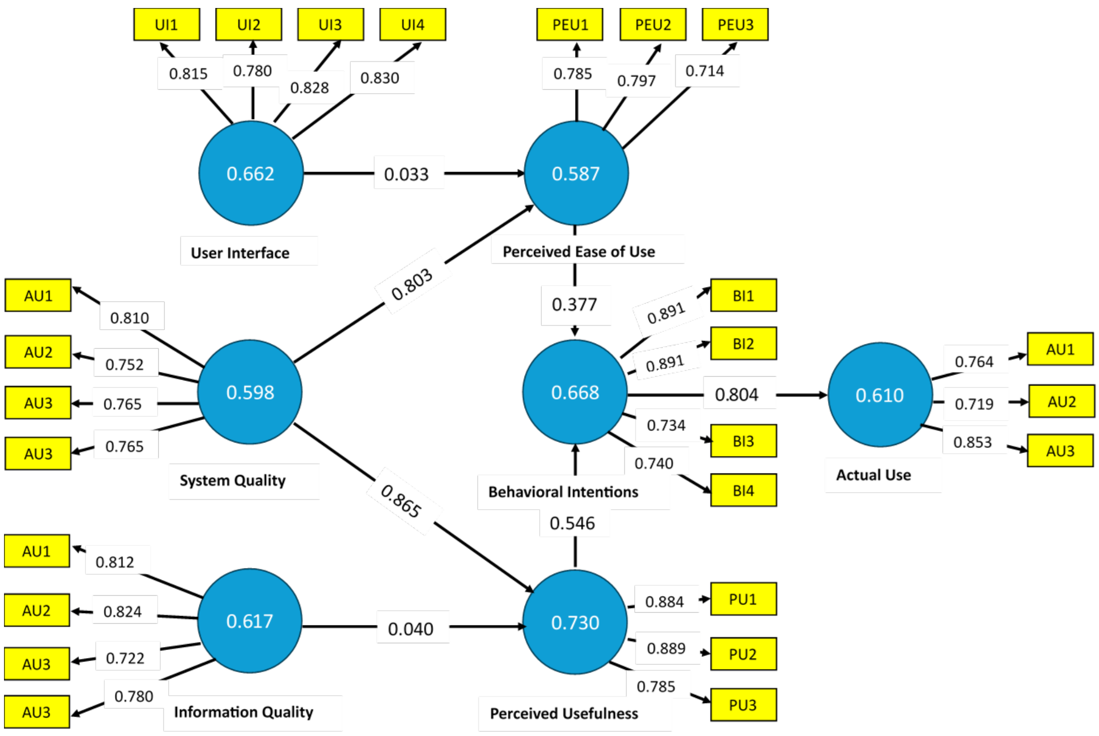

Figure 2: PLS-4 path model

5.1.4. R Square

The values of the latent variables from the R square and Adjusted R square are shown in Table 5. Specific values for the R^2 statistic are significant (R=0.750), moderate (R=0.500), and weak (R=0.250) [46].

The R-square value for the dependent variable "Actual Use" is 0.480, indicating that 48.0% of the variance in actual use can be explained by the independent variables included in the model. This relatively high value suggests that the model has strong explanatory power. Additionally, the adjusted R-square value of 0.478, which accounts for the number of predictors, is very close to the R-square value. This slight decrease indicates that the model's explanatory power is robust and not significantly inflated by the number of predictors. Overall, the model demonstrates a good fit for predicting actual use, implying that the selected independent variables effectively explain a substantial portion of the variance in this outcome. For "Behavioural Intentions," the R-square value is 0.351, meaning that the model explains 35.1% of the variance in behavioural intentions. This represents a moderate level of explanatory power. The adjusted R-square value is slightly lower at 0.345, suggesting that the model's fit is not excessively influenced by the number of predictors included. Although the model explains a significant portion of the variance, the moderate fit implies that other factors not captured by the current independent variables may also play an essential role in shaping behavioural intentions. Further research could explore additional predictors to enhance the model's explanatory capability.

The R-square value for "Perceived Usefulness" is 0.257, indicating that the independent variables in the model account for 25.7% of the variance in perceived usefulness. This relatively lower value suggests that while the model explains a fair amount of variance, a significant portion remains unexplained. The adjusted R-square value of 0.249 reflects a slight decrease, reinforcing that the number of predictors moderately influences the model's power. This finding suggests that other variables not included in the model may significantly impact perceived usefulness. Identifying and incorporating these additional factors could improve the models explain this outcome.

The R-square value for "Perceive" Ease of Use" is not "low" at 0.016, indicating that the independent variables explain only 1.6% of the variance in perceived ease of use. This lack of fit is further emphasized by the adjusted R-square value, which decreases to 0.006 after accounting for the number of predictors. These values suggest that the current model has minimal explanatory power for perceived ease of use, implying that the independent variables included are not substantial predictors of this outcome. Consequently, other significant factors influencing perceived ease of use are missing from the model. Further research should aim to identify and include these factors to develop a more robust model for this variable.

5.2. Assessment of Structural Model

One of the most important aspects of evaluative studies is to analyze relationships and pathways between different variables. Figure 3 below depicts a structural model showing the relationship between variables at a 0.05 significance level.

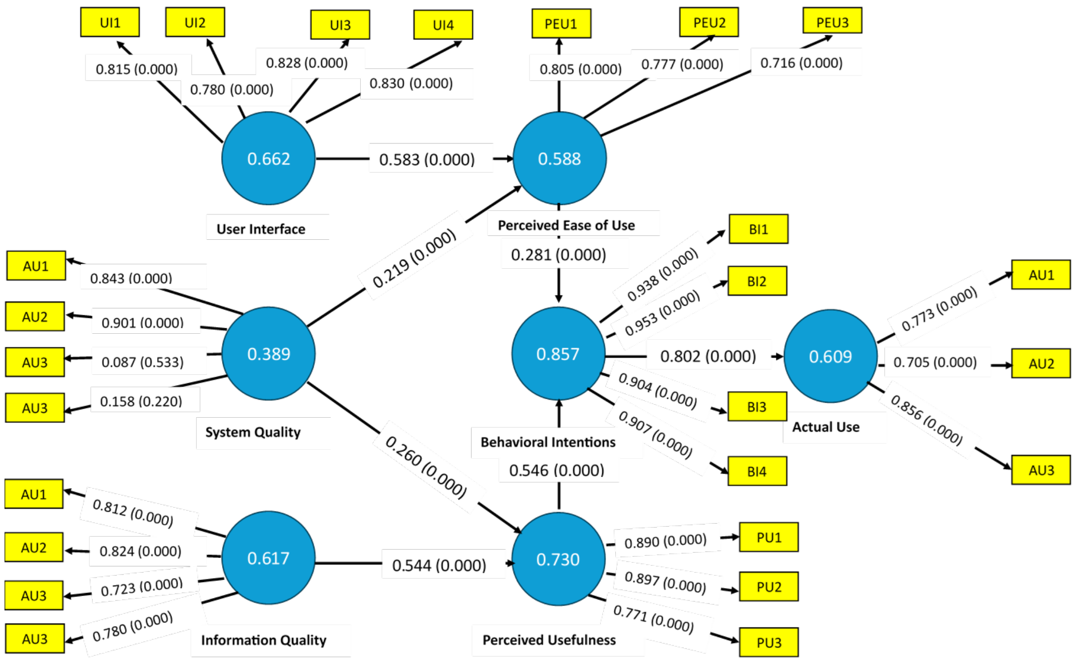

Figure 3. Structural model

The model demonstrates that user interface directly impacts Perceived Ease of Use with path coefficient = 0.523 ($p < 0.000$). All this says is a more usable UI results in higher perceived ease of use. PHU influenced PEU greatly with the path coefficient of 0.289(p < 0,000), which means that better system quality leads the customer to a significant perception that IT will be an easy-to-use editorial board. The direct path from information quality significantly affects perceived usefulness with a size of 0.544 ($P < 0.000$). This strong relationship indicates sufficient information adds the necessary quality to increase the system's effectiveness. System quality directly affects PU (path coefficient = 0.369 $p < 0.000$), meaning the user perceives a well-functioning system as more practical. The fourth dimension is Perceived Ease of Use Path Weight P-value Behavioural Intentions 0.281 ($p < 0.000$). This establishes that users are more likely to use a system if they think it is easy. On the other hand, perceived ease of use (PEU) influences actual usage indirectly through behavioural intentions (BI), which acts as a cognitive attitude driving user engagement. As shown in Table 3, BI mediates the direct effects of PEU on user engagement.

The Perceived Usefulness significantly influences the Behavioural Intentions, where Attitude with 0.540 ($p < 0.000$) Path Coefficient and final, Actual Use of it by a coefficient path is shown to be significant at the value of approximately 489 89(p <001). These relationships imply that users with a positive perception of system usefulness are likelier to hold favourable behavioural intentions and use the system. These findings underscore the critical role of an individual's perception of how useful it is (PU) in using the specific system and the reinforcing indirect effects of PU on AU through BI.

Additionally, Behavioural Intentions have a book path effect of 0.773 ($P < 0.000$) on Actual Use. This association points to motivational constructs, suggesting that users' motivation to use the system matters and predicts their actual usage behaviour. The path coefficient was high, emphasizing the relevance of appraising and nurturing positive behavioural intentions for augmenting system use. However, Table 6 provides the result of the direct, indirect, and mediation effects observed in the structural model.

Table 5. Path testing

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Direct Effect					
Behavioural Intentions -> Actual Use	0.802	0.804	0.028	28.600	0.000
Information Quality -> Perceived Usefulness	0.544	0.545	0.050	10.823	0.000
Perceived Usefulness -> Behavioural Intentions	0.624	0.622	0.061	10.244	0.000
Perceived Ease of Use -> Behavioural Intentions	0.281	0.283	0.071	3.943	0.000
System Quality -> Perceived Usefulness	0.260	0.264	0.057	4.535	0.000
System Quality -> Perceived Ease of Use	0.219	0.222	0.055	3.976	0.000
User Interface -> Perceived Ease of Use	0.583	0.584	0.048	12.071	0.000
Indirect Effect					
Information Quality -> Actual Use	0.272	0.273	0.041	6.558	0.000
Information Quality -> Behavioural Intentions	0.339	0.339	0.048	7.039	0.000
Perceived Usefulness -> Actual Use	0.500	0.500	0.055	9.163	0.000
Perceived Ease of Use -> Actual Use	0.225	0.228	0.058	3.872	0.000
System Quality -> Actual Use	0.180	0.183	0.034	5.215	0.000
System Quality -> Behavioural Intentions	0.224	0.227	0.041	5.459	0.000
User Interface -> Actual Use	0.131	0.134	0.038	3.421	0.001
User Interface -> Behavioural Intentions	0.164	0.166	0.047	3.498	0.000
Mediation Effect					
Perceived Usefulness -> Behavioural Intentions -> Actual Use	0.500	0.500	0.055	9.163	0.000
System Quality -> Perceived Ease of Use -> Behavioural Intentions	0.061	0.063	0.023	2.662	0.008
Perceived Ease of Use -> Behavioural Intentions -> Actual Use	0.225	0.228	0.058	3.872	0.000
System Quality -> Perceived Usefulness -> Behavioural Intentions	0.163	0.164	0.040	4.092	0.000
User Interface -> Perceived Ease of Use -> Behavioural Intentions	0.164	0.166	0.047	3.498	0.000
Information Quality -> Perceived Usefulness -> Behavioural Intentions -> Actual Use	0.272	0.273	0.041	6.558	0.000
System Quality -> Perceived Usefulness -> Behavioural Intentions -> Actual Use	0.130	0.132	0.033	3.993	0.000
User Interface -> Perceived Ease of Use -> Behavioural Intentions -> Actual Use	0.131	0.134	0.038	3.421	0.001
Information Quality -> Perceived Usefulness -> Behavioural Intentions	0.339	0.339	0.048	7.039	0.000
System Quality -> Perceived Ease of Use -> Behavioural Intentions -> Actual Use	0.049	0.051	0.019	2.616	0.009

For Direct effects, the path with the most substantial direct effect is from Behavioral Intentions to Actual Use (path coefficient = 0.802, $p < 0.000$), suggesting that users' intention to use a system accurately predicts their actual usage behavior in factual life circumstances. This emphasizes the need to encourage positive behavioral intentions for high system utilization. The quality of Information to Perceived Usefulness (0.544, p-value < 0) Useful of Perceived Usefulness provides the most significant correlation with one mono item Behavioral Intentions (0.624), suggesting that if users believe it to be helpful, they intend to use it ($p < 0.000$). In addition, Perceived Ease of Use directly and moderately influences Behavioral Intentions (0.281, $p < 0.000$), where the usage is essential but not so much as it means this explainer factor does have a little bit on invading into users' intentions areas which construct their intent to use ADHD Humanoid App or vice versa [40]. System Quality influences Perceived Ease of Use (0.219, $p < 0.000$) and Perceived Usefulness (0.260, $P < 0.000$), demonstrating that a system with high quality increases ease of use as well as functional utility expectations. Therefore, User Interface significantly directly impacts Perceived Ease of Use (0.583, $p < 0.000$) and underscores that having an excellent user interface is the key to making a system easy to use.

In Table 5 above, the indirect effects show that the overall data quality affects actual and perceived utility with a coefficient value of.272 ($p <0.000$). This underlines the path of quality information to perceived usefulness and usefulness to behavioral attitude (intentions) [40]. Perceived Usefulness in Usefulness effects Actual Use (H4) with a coefficient of.500 ($p <.000$), further supporting our assertion that perceived Usefulness is helpful in adoption. On the other hand, Perceived Ease of Use indirectly affects Actual Use (0.225, $p < 0.000$), supporting that to drive actual usage through behavioral intentions, a system must be easy to use as well. System Quality also positively influences Actual Use (0.180, $p < 0.000$) and behavioral intentions (0.224, $p < 0.000$). Still, through its effects on Perceived Usefulness, the path to use is constructed with System Quality underpinning user experience as a touchstone of digital quality [54]. Hence, the interface will have a direct effect on Actual Use (0.131, p-value <.001) and Behavioral Intentions (0.164, p-value<00, which strongly recommends that a good Interface plays a very vital role in defining user behavior collectively, as shown in figure 3 above).

The effects of mediation further explicate the intricate relations between variables. For example, Perceived Usefulness mediates between Behavioral Intentions and Actual Use (0.500, $p < 0.000$), as well as Perceived Ease of Use mediates between System Quality and Behavioral Intentions (0.061, $p < 0.008$).

This has two significant implications: on one hand, it shows that many factors influence users' perceptions and behaviors (see accounts of mediations), allowing a more complete perspective in studying how these lead to actual system uses. The model also shows that, while direct effects like Behavioral Intentions to Actual Use are substantial [93], it is essential not to be blinded by the power of these individual items as much indirect and mediation effects from first-generation measures still play significant roles in understanding the whole user experience. Knowing these phenomena can inform more specific system designs and information quality improvements that predictably improve the experience with solution engagement variables. Thus, seven hypotheses (H1 – H7) were confirmed in the study; they account for how distinct factors contribute to the actual use of a system. H1 was, therefore, found to be the strongest and most direct relationship in the study; when users intend to use a system, they are highly likely to do so. H2 signifies that high-quality information (e.g., content that is accurate, relevant, and timely) leads users to perceive the system as being more helpful. H3 builds on this by showing that when users find a sound system, they are more likely to use it because they believe that this system will help them achieve their goals. H4- If a system is easy to use, users will be more inclined to adopt it, although this effect is a little weaker than the perceived usefulness. H5 and H6 stress the importance of system quality, revealing that the better the system's quality is, the more perceived useful it is (Shin, 2007), and this higher system quality results in the system being more straightforward to use. Finally, H7 verifies that a user-friendly interface that is easy to understand and aesthetically pleasing significantly improves the ease of use of their system. These findings underscore the point that high-quality information, reliable system performance, and user-friendly design are positive user perceptions, intentions, and use (actual usage).

6. Discussion

Real-world adoption of AI-enabled adaptive e-learning systems in conflict zones, particularly in the Palestinian school's territory, is a complex issue that has received differing views from different academic sources. Yet, a generative set of studies highlights the promise of adaptive e-learning systems guided by AI to transform education in conflict zones through scalable, flexible, and personalized learning. [4] Argued that such systems can adapt educational content to make individual students more engaged with learning results. Similarly, [9] expressed that e-learning as an instructive framework can be a positive factor contributing to and contending effectively with the conventional system through equal exactness in learning quality, however better than expected execution result-wise.

Similarly, [10] claimed that e-learning could provide an opportunity for women at conflict zones to enhance society's socio-cultural and economic deficiencies by delivering education on accessible terms. This can be all the most important in unstable places, where infrastructure and schools can frequently shut down, Similarly, the role of AI-enabled e-learning in sustaining educational continuity has been emphasized by [11] through the use of novel technologies like Zero configuration protocols and TVWS transmission channels, guaranteeing that even distant teachers and pupils could stay connected virtually, allowing instantaneous communication opportunities. For example, [12] confirmed that the Institute of International Health and Education SRIPs Online Educational Program for Displaced Syrian Medical Students States by passed issues such as electricity shortages and infrastructure damage using smartphones with 90% attendance. In line with [19], [37], [13] also endorses more investments in e-learning to ameliorate the catastrophic effects of educational infrastructure demolitions and suggests further implementation of methodological frameworks using ICT that will keep education activities alive even during emergencies. While the dispensation is hopeful of a happy ending, opinions are divided on whether AI-enhanced adaptive e-learning systems would work well in conflict zones. [5] Systems implementations are likely resource-intensive, especially where training and infrastructure are required; however, failure in civil conflict areas can have severe consequences. Unless these fundamental issues are addressed, the potential positive aspects of AI-driven education will never be achieved. Furthermore, [14] added that a reliable ICT facility is essential to drive e-learning as these vital needs could limit its adoption and efficacy. This is, for instance, very appropriate when referring to Gaza and the intricacy of legal improvisation needed for deploying high-level educational technologies in a context with extreme socio-political instability. [18] Similar are the procedural ethical challenges and moral implications, highlighting the importance of inclusive delivery in AI-enabled educational technologies. Their point is that, without focusing on these ethical facets, introducing AI-driven e-learning systems may amplify current disparities and lead to more forms of educational exclusion.

7. Conclusion

Integrating AI-enabled adaptive e-learning systems in conflict zones such as Palestinian schools presents significant opportunities as well as challenges. This study has provided a critical discussion of the existing literature, highlighting agreement and disagreement among researchers regarding the feasibility and effectiveness of these advanced educational technologies.

The literature largely agrees on the transformative potential of AI-driven e-learning systems to enhance academic outcomes by providing personalized, flexible, and scalable learning experiences. These systems can adapt to the unique needs of each student, thereby improving engagement and effectiveness. This is particularly beneficial in conflict zones where traditional educational infrastructure is often disrupted. The examples from various conflict-affected regions, including Saudi Arabia, Central African Republic, and Syria, demonstrate that e-learning can be a viable alternative to traditional education, maintaining continuity and accessibility even amidst instability. However, significant challenges remain in implementing these systems in conflict zones. The need for substantial investment in infrastructure, training, and resources cannot be overstated. Studies have shown that without addressing these foundational requirements, the potential benefits of AI-driven education may not be fully realized. Ethical considerations also play a crucial role, as equitable access to these technologies must be ensured to prevent exacerbating existing inequalities.

Furthermore, the socio-political context of regions like Gaza presents additional barriers that must be navigated to deploy AI-enabled e-learning systems successfully. The need for robust ICT infrastructure, stable internet connectivity, and digital literacy among users are critical factors that influence the adoption and effectiveness of these systems. While AI-enabled adaptive e-learning systems offer a promising solution to the educational challenges in conflict zones, their successful implementation requires a comprehensive approach that addresses infrastructural, socio-political, and ethical issues. Policymakers and educational practitioners must collaborate to create supportive environments that facilitate the adoption of these technologies. Future research should continue to explore context-specific strategies and models that can enhance the effectiveness and accessibility of AI-driven educational solutions in conflict-affected areas. By doing so, it is possible to harness the full potential of AI in transforming education and fostering resilience in some of the world's most challenging environments.

This paper contributes to the theoretical body of knowledge on how conflict zones encourage the adoption of AI-enabled adaptive e-learning systems as educational technology in Palestinian schools. It combines the Extended TAM and DeLone and McLean's Information Systems Success Model to provide a rich model that explains why AI-driven e-learning systems can be adopted in such adverse conditions. All these factors indirectly impact behavioral intentions and usage behavior, suggesting the importance of an integrated framework for discovering their relationship.

Additionally, the study furthers the use of theoretical models by defining them within socio-political and economic conditions specific to conflict zones (e.g., social/political turbulence, infrastructure shortages, and resource limitations). Using data from Palestinian schools and through empirical validation, it offers strong evidence on relationships among key constructs within the context of AI-enabled e-learning systems, which not only confirms the hypothesized relationship but also establishes a pivotal role attributed to perceived ease of use and perceived usefulness in fostering behavioral intentions and actual usage. Moreover, the study adds to this general discussion of AI in education by offering a detailed illustration of how focusing on either ethical or equity concerns associated with deploying commercially available and plausible scenarios for an adaptive learning technology can inform these debates by illustrating what is at stake when such technologies are introduced. This paper links these theoretical contributions with practical implications for policymakers and educational practitioners, offering insights into key areas to design or implement such systems in the middle of conflict zones as well as inform effective supportive policies and practices that foster e-learning technologies adoptions and its impact on teaching/learning within those challenging contexts.

Based on the paper findings, important practical considerations for application of AI-enabled adaptive e-learning system to conflict zones especially in Palestinian schools. These insights can help inform policymakers and educational practitioners in creating more effective, inclusive learning environments. The first is with robust ICT infrastructure to support the deployment and maintenance of these advanced e-learning systems. Stable internet availability and access to right digital components like pro-scientific calculators further adds feasibility and productivity to such mission plans. Aditionally, there is a need to train educators and students as well on how to use AI-driven e-learning platforms., alongside increasing digital literacy and providing ongoing support to troubleshoot any technical problems. Also, there is also a need to address ethical considerations and ensure that technology is distributed equitably so as not to further widen the inequality gap in education. This calls policymakers to implement inclusive strategies that support all students, particularly those who are least advantaged. Lastly, cooperation between governments and local schools can better uphold the right ecosystem around AI-based e-learning systems to complement their sustainability.

This paper provides valuable information, but several limitations need to be addressed. This research is context-specific and culminates in Palestinian schools; thus, the findings may be generalizable to other conflict zones with different socio-political and economic statuses.

Future research could replicate such studies with experience exchange between conflict-affected regions. Second, the analysis consists of numerical data that may not fully detail users' experiences and beliefs. Incorporating qualitative methods, such as interviews and focus groups, into the study can provide a more comprehensive understanding of the factors influencing AI-enabled e-learning systems in war zones, thereby enhancing inclusivity and offering deeper insights. The emerging nature of AI and educational technologies means that new developments may rapidly obsolete these results. The field requires ongoing research to inform hair-trigger responses about how technological changes affect education in conflict settings. Finally, more longitudinal research is needed to evaluate the effects of AI-enabled adaptive e-learning systems on educational and resilience outcomes in conflict-affected contexts across time scales to provide a better perspective regarding their overall impassiveness and sustainability.

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