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The Role of AI-Driven Adaptive Multimedia Systems on Personalized Learning Paths

Rabaab D. Alsaffar[1*]

College of Basic Education, The Public Authority for Applied Education and Training, Kuwait
rd.alsaffar@paaet.edu.kw
[*]Corresponding author

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Abstract: This study examines how AI-driven adaptive multimedia systems shape personalized learning paths by integrating three theoretical perspectives: the Technology Acceptance Model (TAM), Cognitive Load Theory (CLT), and Constructivist Learning Theory. Using structural equation modeling to analyse survey data from 296 students across Kuwait's Basic Education Colleges, we identify Learner Digital Readiness as the strongest predictor of learning path optimization. The findings demonstrate significant roles for both AI System Quality and Perceived Personalization Effectiveness, while revealing that conventional Multimedia Interactivity alone does not significantly contribute to optimization in adaptive environments. The research makes two key contributions: (1) advancing a unified theoretical framework that bridges technological, cognitive, and pedagogical dimensions of personalized learning, and (2) providing empirical evidence for practical implementation strategies, particularly the need for digital readiness development, transparent system design, and adaptive onboarding processes. These insights offer valuable guidance for educators and designers creating AI-enhanced learning environments, particularly in contexts where digital literacy varies widely among learners.

Keywords: Personalized Learning, Digital Readiness, AI system quality, Learning engagement, Multimedia interactivity

1. Introduction

The global education sector is undergoing a profound transformation as artificial intelligence (AI) becomes increasingly embedded in learning ecosystems. Among the most promising developments are AI-driven adaptive multimedia systems, which dynamically tailor educational content and pathways based on real-time analysis of learner performance, preferences, and cognitive patterns. These intelligent systems promise to revolutionize education by delivering truly personalized learning experiences that enhance engagement, efficiency, and learner autonomy (Cho, 2022; Rane et al., 2023). However, as educational institutions worldwide race to adopt these technologies, critical questions remain about how various technological and human factors interact to optimize learning outcomes in AI-enhanced environments.

Kuwait's educational landscape presents a particularly compelling context for investigating these dynamics. The country's Basic Education Colleges, under the Public Authority for Applied Education and Training (PAAET), are actively pursuing digital transformation initiatives that incorporate AI technologies. This transition occurs against a backdrop of varying digital readiness among students and evolving pedagogical approaches to technology integration. The Kuwaiti context thus offers valuable insights into the challenges and opportunities of implementing AI-driven personalization in educational systems undergoing digital transformation.

This study seeks to advance understanding through an integrated theoretical framework that combines three foundational perspectives: the Technology Acceptance Model (Venkatesh & Bala, 2008), Cognitive Load Theory (Sweller, 1994), and Constructivist Learning Theory (Piaget, 1970). Building on these foundations and recent syntheses of AI in education (Zawacki-Richter et al., 2019), we examine how AI system quality, multimedia interactivity, and learner digital readiness collectively influence personalized learning outcomes, with particular attention to the mediating roles of engagement and perceived personalization effectiveness.

The research addresses two significant gaps in current literature. First, while numerous studies have examined individual components of AI-enhanced learning systems, few have investigated how these elements interact within a comprehensive framework that includes both system-driven and learner-centric variables. As noted by Abbasi et al. (2024) and Chen et al. (2020), existing design research in AI tends to be fragmented, often focusing on technological affordances without integrating learner behavior, engagement, and cognitive dynamics into a unified model. Second, there remains limited understanding of how learners in developing educational systems perceive and engage with AI-driven personalization features, despite increasing deployment of these technologies. This issue is underscored by Admeur and Attariuas (2024) and Bitegeko et al. (2024), who emphasize the importance of aligning AI tools with learners' digital competencies and socio-educational contexts. Our study contributes to filling these gaps by developing and testing a structural model that captures the complex interplay between technological capabilities and human factors in personalized learning environments, particularly in the underexplored context of Kuwaiti Basic Education institutions.

Through this investigation, by developing and empirically testing an integrative model, we aim to provide both theoretical insights and practical guidance for educators and policymakers navigating the challenges of AI integration in higher education. The findings will be particularly relevant for institutions, like those in Kuwait, that are balancing technological innovation with the need to ensure equitable access and effective learning experiences for students with diverse digital competencies.

2. Theoretical Background

This study examines AI-driven adaptive multimedia systems in personalized learning through a model integrating Technology Acceptance Model (TAM) (Davis, 1989) and Cognitive Load Theory (CLT) (Sweller, 1994). These theories conceptualize relationships among predictors (AI System Quality, Multimedia Interactivity, Learner Digital Readiness), mediators (Learning Engagement, Perceived Personalization Effectiveness), and outcome (Learning Path Optimization). TAM explains technology adoption via perceived usefulness and ease of use. Here, AI System Quality (AISQ) and Learner Digital Readiness (LDR) reflect these constructs, influencing engagement and learning optimization (Venkatesh & Bala, 2008). Prior work supports TAM's applicability to AI-based learning (Li, 2023). Two key constructs of this research, AI System Quality (AISQ) and Learner Digital Readiness (LDR) align with TAM's core components: perceived usefulness and ease of use. AISQ encompasses the system's reliability, responsiveness, and overall effectiveness, shaping students' perceptions of its utility. Meanwhile, LDR reflects learners' digital competence and confidence, influencing their ability to navigate the system effortlessly and their willingness to engage with technology (Blayone, 2018, October). Together, AISQ and LDR play a crucial role in fostering Learning Engagement (LRE) and Perceived Personalization Effectiveness (PPE) by building trust and reinforcing the perceived value of the learning experience. When AISQ and LDR are strong, students exhibit higher engagement and acceptance, ultimately leading to improved Learning Path Optimization (LPO) (Mutambik, 2024). By elucidating the progression from initial exposure to AI-enhanced learning environments to active, personalized engagement, TAM highlights the interplay between system attributes and user readiness (Wu et al., 2024). This underscores the importance of both technological design and learners' preparedness in achieving seamless integration and maximizing educational outcomes in technology-driven settings.

On the other hand, Cognitive Load Theory (CLT) highlights managing cognitive load for effective learning. MMI and PPE align with CLT, as adaptive systems reduce extraneous load by tailoring content (Lee & Hughes, 2019). PPE enhances comprehension and outcomes in AI educational video assistants utilizing large language models (AlShaikh et al., 2024). In this study, Multimedia Interactivity (MMI) and Perceived Personalization Effectiveness (PPE) are instrumental in minimizing extraneous cognitive load by adjusting content complexity and presentation based on learners' needs (Lin et al., 2024). MMI incorporates interactive elements such as quizzes, videos, and feedback mechanisms that, when thoughtfully designed, enhance learner control and focus. PPE ensures that adaptive systems dynamically adjust pacing, content, and difficulty levels, allowing learners to efficiently allocate cognitive resources. Furthermore, Learner Digital Readiness (LDR) serves as a moderating factor, enabling digitally proficient students to engage with AI-driven systems seamlessly while mitigating cognitive overload caused by technological friction (Hidayat-ur-Rehman, 2024). Collectively, these elements foster Learning Engagement (LRE) by reducing frustration and deepening immersion, ultimately leading to enhanced Learning Path Optimization (LPO). CLT thus provides a strong theoretical foundation for the development of AI-powered personalized learning systems that cater to learners' cognitive capabilities. By facilitating effective personalization, these systems not only improve comprehension but also minimize unnecessary cognitive effort, making learning more efficient and meaningful.

3. Literature Review

The rapid evolution of AI has transformed personalized learning, with adaptive multimedia systems now playing a pivotal role in delivering tailored educational experiences. Rane et al., (2023) have highlighted how AI-driven platforms enhance learner autonomy by continuously adapting content based on real-time performance and preferences. These systems utilize sophisticated analytics to refine instructional pathways, ensuring alignment with individual cognitive needs. Yet, while their technical capabilities are well-documented, less attention has been paid to how learners perceive AI system quality, particularly across different digital learning contexts, and how these perceptions ultimately shape educational success.

Multimedia interactivity further enriches personalized learning by balancing engagement and cognitive load. Well-designed interactive elements such as simulations, scenario-based exercises, and responsive feedback have been shown to deepen comprehension and sustain motivation (Kapp, 2025; Rutten & Brouwer-Truijen, 2025). However, despite established principles for multimedia design, empirical research has scarcely explored how interactivity functions as a structural component within AI-adaptive systems, leaving unanswered questions about its synergistic effects on personalized learning outcomes.

Equally critical is the concept of Learner Digital Readiness (LDR), which encompasses digital literacy, self-regulation, and comfort with technology. Blayone (2018, October) underscore that these competencies are strong predictors of success in digital learning environments. Learners who are more digitally prepared not only navigate platforms more effectively but also exhibit greater openness to AI-driven personalization. Role of PPE and LRE has been observed in boosting student motivation to learning and active participation, thereby optimizing learning trajectories (Wu et al., 2024).

Despite these advancements, the literature remains siloed, often examining factors like AI system quality, multimedia interactivity, and digital readiness in isolation rather than as interconnected components of a unified learning ecosystem. Few studies have investigated how these predictors interact with mediators such as engagement and perceived personalization to collectively influence learning outcomes. This study addresses that gap by proposing and testing an integrated structural model that captures the dynamic interplay of these variables within AI-adaptive environments. In doing so, it offers a more nuanced framework for understanding how technology, pedagogy, and learner attributes converge to shape the future of personalized education.

4. Research Methodology

The research methodology is based on the positivism paradigm and hence quantitative research approach has been used. The details are as follows.

4.1 The Hypothetical Model

Building upon established theoretical frameworks and prior empirical studies across diverse geographical and educational contexts, we developed a conceptual model to examine the relationships between key research constructs. The following sections elaborate on each of these proposed relationships.

4.1.1 Relationship between AISQ and LRE

The interplay between AISQ and LRE has become increasingly important in digital education owing to the role they play in modern higher education. High-quality AI systems characterized by accuracy, responsiveness, and personalization can enhance learner motivation and cognitive involvement through features like adaptive pacing and tailored pathways (Halkiopoulos & Gkintoni, 2024). However, concerns exist about potential over-reliance reducing learner autonomy (Selwyn, 2019), while misaligned recommendations may undermine engagement regardless of technical sophistication (Mohebbi, 2025). Thus, AISQ's impact on LRE appears contingent on both user trust and alignment with individual learning needs. Given these contrasting perspectives, we hypothesize:

H1: AISQ has a positive and significant relationship with LRE.

4.1.2 Relationship between AISQ and PPE

Yet the relationship cannot be taken for granted. Research reveals that even technically advanced systems can miss the mark if their personalization does not resonate with a learner's expectations or preferred ways of learning (Zawacki-Richter et al., 2019). Many learners do not fully grasp how AI personalization works behind the scenes, which can breed skepticism when recommendations do not match their self-perception (George, 2023).

Ultimately, while high-quality AI lays the foundation for effective personalization, its success depends on three human factors: how transparent the system's logic appears, how well users understand it, and whether the personalized content feels genuinely relevant to their learning journey.

Only a longitudinal investigation can help understand this relationship and hence we hypothesize:

H2: AISQ has a positive and significant relationship with PPE.

4.1.3 Relationship between MMI and LRE

Interactive multimedia has transformed modern learning environments, offering dynamic ways to capture and sustain learner engagement. Simulations, scenario-based activities, and responsive feedback are found to stimulate cognitive, emotional, and behavioral involvement by encouraging active participation and providing immediate reinforcement (Battista, 2017; Zhang et al., 2006).

However, the relationship between MMI and LRE is nuanced. Excessive or poorly implemented interactive elements can overwhelm learners, creating cognitive strain that hinders rather than helps (Chen & Wu, 2015; Shalaby, 2024). Moreover, individual differences such as digital literacy and prior experience influence how learners respond to interactive features, meaning a 'one-size-fits-all' approach may leave some students behind (Antonenko et al., 2020).

These contrasting views suggest MMI's impact on LRE depends heavily on contextual factors warranting empirical studies to identify key moderators like psychological safety and leadership support. Hence, we hypothesize the following.

H3: MMI has a positive and significant relationship with LRE.

4.1.4 Relationship between MMI and PPE

The relationship between MMI and PPE lies in how learners experience and interpret adaptive learning environments. Well-designed interactive elements such as responsive quizzes, choose-your-own-path content, and learner-directed navigation can create a powerful sense of individualized learning (Poth, 2022; Stewart & Sheppard, 2021). When students feel they can influence their learning path through these interactions, they are more likely to view the system as genuinely tailored to their needs.

However, research also reveals important caveats. Interactive features that simply repackage static content without true adaptivity often fail to convince learners of meaningful personalization (Zawacki-Richter et al., 2019). Similarly, generic interactivity that does not reflect individual progress or preferences may be perceived as gimmicky rather than purposeful (Chen et al., 2020). Thus, there are contrasting views and findings about this relationship, and hence, we propose the following hypothesis:

H4: MMI has a positive and significant relationship with PPE.

4.1.5 Relationship between LDR and LRE

LDR plays a pivotal role in shaping their LRE within technology-enhanced learning environments. Research demonstrates that digitally competent individuals exhibit greater confidence and motivation, enabling more active participation in online tasks and peer collaboration (Martzoukouet al., 2020). Strong digital skills facilitate platform navigation, minimizing frustration and cognitive load. However, digital proficiency alone cannot sustain engagement when content lacks relevance or fails to resonate emotionally (Hollebeek & Macky, 2019). Thus, while LDR serves as a critical foundation for LRE, its full potential is realized only when coupled with thoughtful, engaging instructional design that addresses both cognitive and affective learning dimensions. Given these mixed outcomes, empirical testing is crucial to determine when LDR has a statistically significant relationship with LRE, and hence we postulated the following hypothesis.

H5: LDR has a positive and significant relationship with LRE.

4.1.6 Relationship between LDR and PPE

LDR significantly shapes perceptions of PPE in adaptive learning systems. Digitally proficient learners demonstrate greater capacity to utilize AI-driven features, recognize tailored content, and adapt their learning strategies accordingly (Rane et al., 2023). However, even skilled users may undervalue personalization when system adaptations lack transparency or noticeable impact (Shin, 2020). The relationship between LDR and PPE remains complex, as effective personalization requires both learner competence and clear system communication about adaptation mechanisms. This underscores the need for empirical investigation, particularly in AI-enhanced environments where personalization algorithms may not be inherently transparent to users, and hence the following hypothesis.

H6: LDR has a positive and significant relationship with PPE.

4.1.7 Relationship between LRE and LPO

Engaged learners demonstrate greater capacity for navigating personalized learning trajectories effectively. When students invest cognitive effort, emotional energy, and consistent behavioural participation, they tend to: (1) utilize system feedback more productively, (2) maintain goal-directed progress, and (3) achieve deeper learning outcomes (Fredricks et al., 2004; Li & Lerner, 2013). This active engagement aligns with the fundamental processes underlying optimized learning paths. However, engagement alone cannot compensate for system limitations. Poorly designed adaptive mechanisms may fail to translate learner involvement into optimal pathways (Werners et al., 2021), while mismatches between personalization and learner needs can derail even highly motivated students (Admeur & Attariuas, 2024). These contingencies highlight the need to examine how engagement interacts with system capabilities to produce truly optimized learning experiences. Given these complexities, empirical testing is essential to determine when and how LRE truly enhances LPO, accounting for contextual factors that may strengthen or weaken this relationship, and hence the following hypothesis:

H7: LRE has a positive and significant relationship with LPO.

4.1.8 Relationship between PPE and LPO

Learners' perceptions of PPE serve as a critical catalyst for LPO. When students believe content adapts meaningfully to their needs, they demonstrate greater motivation, focus, and progression efficiency (Cho, 2022). This perceived alignment between system adaptations and individual goals enhances learning trajectory quality in AI-driven environments. Yet significant caveats exist. Opaque personalization mechanisms or mismatches with learner preferences can breed disengagement (Firat, 2023), while superficial adaptations based on poor data may render perceived benefits ineffective (Zawacki-Richter et al., 2019). These contingencies suggest PPE's impact on LPO depends heavily on both system transparency and adaptation depth, warranting empirical validation across diverse learning contexts and hence the following hypothesis:

H8: PPE has a positive and significant relationship with LPO.

4.1.9 Relationship between AISQ and LPO

The impact of AISQ on LPO stems from learners' ability to navigate and benefit from adaptive learning environments. Technically robust systems demonstrating precise recommendations, responsive feedback, and reliable personalization foster learner trust and facilitate more efficient progress through content (Chen et al., 2020; Gm et al., 2024). These capabilities enable systems to guide learners along trajectories that align with their evolving competencies and goals. However, optimization depends on more than technical excellence. When system logic remains opaque or fails to account for diverse learning contexts, even sophisticated AI may produce suboptimal pathways (Abbasiet al., 2024; Zawacki-Richter et al., 2019). This suggests AISQ's relationship with LPO is mediated by both the transparency of adaptive mechanisms and the system's capacity to accommodate varied learner needs - propositions requiring empirical validation, and hence the following hypothesis.

H9: AISQ has a positive and significant relationship with LPO.

4.1.10 Relationship between MMI and LPO

MMI can significantly influence LPO by empowering learners to navigate content in ways that align with their individual needs. Well-designed interactive features including exploratory simulations, decision-based scenarios, and responsive visualizations promote active learning while allowing students to control pacing and content exploration (Zhang et al., 2006). This enhanced agency facilitates more efficient knowledge acquisition and personalized progression among students. However, the effectiveness of MMI depends on thoughtful implementation. When interactivity functions independently of adaptive learning mechanisms, it risks creating fragmented experiences that hinder rather than help (Chen & Wu, 2015). Similarly, excessive or poorly structured interactive elements may overwhelm learners with lower digital readiness (Sun & Rueda, 2012). These findings suggest MMI's contribution to LPO is maximized when interactivity: (1) integrates with personalized learning algorithms, (2) maintains clear instructional purpose, and (3) accommodates varying learner capabilities, and further empirical investigation is required to provide concrete proof to the relationship. Hence the following hypothesis is postulated.

H10: MMI has a positive and significant relationship with LPO.

4.1.11 Relationship between LDR and LPO

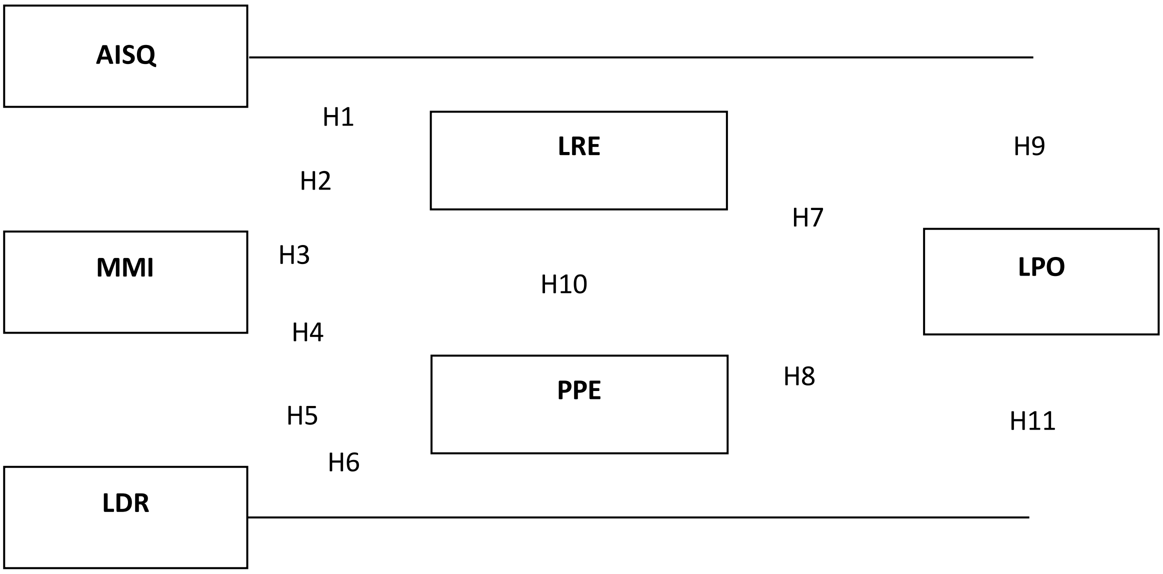
LDR serves as a critical enabler for LPO in AI-enhanced educational environments. Digitally proficient learners possessing technical fluency, self-regulation skills, and adaptive learning strategies demonstrate superior ability to: (1) navigate personalized interfaces, (2) interpret system-generated feedback, and (3) adjust their learning trajectory accordingly (Hung et al., 2010; Wei, 2024). This synergy between user capability and system functionality creates conditions for efficient, goal-aligned progression. However, the relationship faces important boundary conditions. When adaptive systems employ rigid algorithms or superficial personalization, even highly digitally-ready learners encounter artificial ceilings on their potential optimization (Macías-Escrivá et al., 2013). This suggests LDR's impact on LPO is contingent upon both learner competencies and system adaptability, a dynamic requiring rigorous examination in contemporary AI-driven learning contexts, and hence the following hypothesis.

H11: LDR has a positive and significant relationship with LPO.

The hypothetical model is depicted in Figure 1.

Figure 1

The Hypothetical Model



Legend:
AISQ = AI System Quality; MMI = Multimedia Interactivity; LDR = Learner Digital Readiness; LRE= Learning Engagement; PPE = Perceived Personalization Effectiveness; LPO = Learning Path Optimization

4.2 Metric Development

For this study, we adopted established measurement scales to assess the key constructs, modifying items as needed to align with our research context while preserving conceptual integrity. To verify the psychometric properties of these adapted measures, we conducted confirmatory factor analysis (CFA), which supported their reliability and validity. The dimensions, meaning, scales and contributing authors, and items chosen are provided in Table 1. Initially 6 items were chosen for each dimension from the standard scales and through factor reduction they were reduced to 3 items each through the pilot study with a sample size of 30 (about 10-20% of the primary sample size) (Julious, 2005).

Table 1

Dimension, Meaning, Scales and Contributing authors, and Items chosen

Dimension	Meaning	Scales	Contributing Authors	Items chosen
1. AI System Quality (AISQ)	The perceived accuracy, reliability, and responsiveness of the AI-based learning system.	System Quality Scale, AI Quality Perception Scale, and TAM3 Scale	Alshahrani et al. (2019); Chen et al. (2020); Petter et al., (2008); Venkatesh & Bala (2008)	1. The AI system recommends learning materials that are accurate and helpful for my studies. 2. When I interact with the system, it responds quickly and without delay. 3. I feel I can depend on this AI system to support my learning needs. 4. The system works equally well across all my different course subjects. 5. The suggestions I receive are relevant to what I have studied before. 6. The system operates smoothly without glitches or technical problems.
2. Multimedia Interactivity (MMI)	The degree to which multimedia content allows learner control, participation, and feedback.	Interactive Multimedia Learning Scale, Multimedia Learning Principles Scale, and Interactive Learning Environments Scale	Zhang et al. (2006); Mayer (2005); Moreno & Mayer (2007)	7. The learning materials include engaging videos, quizzes, or simulations that I can interact with. 8. I can choose different learning paths through the multimedia content. 9. I receive immediate feedback when completing interactive exercises. 10. I can pause, rewind, or skip sections in multimedia lessons as needed. 11. The content includes questions or activities that allow me to actively participate. 12. The interactive features help me better understand the course material.
3. Learner Digital	The student's preparedness, confidence, and ability to use digital tools effectively.	Online Learning Readiness Scale, Digital Literacy and Learning	Field (1089); Hung et al. (2010); Tang et al. (2021)	13. I feel confident using digital platforms for my college coursework.

Dimension	Meaning	Scales	Contributing Authors	Items chosen
Readiness (LDR)		Readiness Scale, and Self-Directed Learning with Technology Scale		14. I can troubleshoot basic technical issues when using online learning systems. 15. I can easily find and navigate through digital learning materials. 16. I know how to use the various digital tools (e.g., apps, learning software) required for my classes. 17. I effectively organize my online coursework and deadlines using digital tools. 18. I can independently learn through digital platforms with minimal assistance.
4. Learning Engagement (LRE)	The learner's cognitive, emotional, and behavioral involvement in the learning process.	Student Engagement Scale, E-learning Engagement Scale, and Online Learning Engagement Scale	Fredricks et al. (2004); Jung et al., (2015); Wang et al. (2022)	19. I maintain good concentration when using AI-powered learning tools. 20. I find myself genuinely interested and engaged during online learning activities. 21. I consistently put forth my best effort when completing digital learning tasks. 22. I actively contribute to online discussions and collaborative activities. 23. Interactive technology presentations increase my motivation to learn. 24. I often continue exploring learning materials independently after sessions conclude.
5. Perceived Personalization	The learner's perception of how well the system adapts to their needs and preferences.	Perceived Personalization Scale, Personalized Learning Effectiveness Scale, and	Li (2016); Wang et al. (2022); Zawacki-Richter et al. (2019)	25. The system consistently recommends content that aligns with my learning needs.

Dimension	Meaning	Scales	Contributing Authors	Items chosen
Effectiveness (PPE)		AI-Based Adaptivity Perception Scale		26. The difficulty level of materials adapts well to my current understanding. 27. The pacing automatically adjusts to match my learning progress. 28. Content selections reflect both my performance history and personal interests. 29. Suggested activities directly support my specific learning objectives. 30. This platform provides better personalization than conventional teaching approaches.
6. Learning Path Optimization (LPO)	The effectiveness and efficiency of the learner's personalized learning journey.	AI-Based Learning Effectiveness Scale, Adaptive Learning Outcomes Scale, and Learning Path Adaptiveness and Utility Scale	Chen et al. (2020); Chou et al., (2022); Wang et al. (2022)	31. The AI system provides a well-organized and logical learning progression. 32. I can follow lesson sequences that optimize my learning efficiency. 33. The system effectively directs me to content that enhances my skills/knowledge. 34. My study time feels productive and well-utilized on this platform. 35. The system accelerates my progress toward achieving learning objectives. 36. The platform's approach aligns perfectly with my optimal learning style.

4.3 The Sampling Design

Convenience sampling technique was adopted in this research to select the sample for study. This decision is driven by the accessibility and expediency it offers, aligning with the research's objectives and the available resources. The target population comprises the students of basic education studying in Colleges of Basic Education (CBE) in Kuwait. CBE is operated by the government's The Public Authority for Applied Education and Training (PAAET) and is part of the nation's applied education sector. There are about 20,000 students under this co-education system so obtaining the unique identity number of each of the students for probability sampling is not very practicable hence non-probability sampling is used in this research

The sample size of 296 respondents determined through convenience sampling strikes a balance between practical considerations and the need for an adequately representative dataset for hypothesis testing. The students from CBE were contacted through the consent of Student Welfare Office. Individuals were contacted through mail and calls, providing them with information about the research's purpose and procedures, and participation will be entirely voluntary. This approach emphasizes the autonomy and willingness of respondents to contribute to the survey, fostering a more genuine and engaged response from the respondents.

Based on the nature of this research, students chosen for data collection included 6 departments, namely Department of Educational Technology (50 students), Department of Curriculum and Teaching Methods (48 students), Computer Department (50 students), Department of English Language (48 students), Department of Science (50 students), and Department of Mathematics (50 students).

Regarding the appropriateness of sample size, while 200 is an adequate sample from the SEM point of view (Hair et al., 2013), one more option would be to use about 10 observations per estimated parameter (Wolf et al., 2013). The sample size selected meets both the criteria. The G-Power test was used to confirm the sample size adequacy. For the effect size (f^2) = 0.3 (medium effect), alpha error probability (α) = 0.05 the G-Power ($1 - \beta$) for the sample of 296 was found to be 0.99 confirming the sample size adequacy.

In line with ethical considerations, the participation was declared to be completely voluntary, and the respondent was given the option to exit at any point of participation if the process was found to be stressful or inconvenient. Thus, ethical clearance of any kind was not required for this research. Moreover, it was clearly declared at the beginning of the questionnaire that no part of the data or information would be used for any purpose other than research. Thus, this sampling design aimed to provide a robust foundation for the quantitative investigation of this research.

5. Results and Analysis

Results are classified into descriptive statistics and inferential statistics. The first part is basically the measurement model, and the second part is the structural equation modelling. These are discussed in the following paragraphs.

5.1 The Measurement Model

The measurement model demonstrated strong psychometric properties across all validity and reliability tests. The items shown in the tables and figure are the ones retained after the factors reduction through confirmatory factor analysis (CFA). Internal consistency was excellent, with both Cronbach's alpha (0.82-0.93) and rho_A values (0.82-0.93) surpassing the 0.70 benchmark (Table ;cutoff of 0.7; Taber, 2018). Composite reliability scores (0.89–0.96) further confirmed the model's robustness (cutoff of 0.6; Mustafa et al., 2020). Convergent validity was supported by high AVE values (0.55–0.77), exceeding the 0.50 threshold (Shrestha, 2021). Discriminant validity, evaluated via the Fornell-Larcker criterion, showed that each construct's AVE square root exceeded its correlations with other constructs (Ahmad et al., 2016). These results collectively confirm that the model is statistically sound for structural analysis.

The R-squared values of 0.652, 0.596, and 0.721 for endogenous variables LRE, PPE, and LPO respectively, indicate that more than 59.6% of the variance is explained by the predictors, confirming that the model fit is good enough to predict the relationships between the variables (cut off 10%, Purwanto & Sudargini, 2021).

Table 3

Reliability and Validity

Construct	Items	Factor loadings	Cronbach's alpha	Rho_a	Composite reliability	Average variance extracted (AVE)
AISQ	AISQ1	0.90	0.89	0.89	0.93	0.74
	AISQ2	0.93				
	AISQ3	0.89				
LDR	**LDR1**	0.93	0.91	0.91	0.94	0.73
	LDR2	0.92				
	LDR4	0.92				
LPO	**LPO4**	0.88	0.88	0.88	0.92	0.55
	LPO5	0.93				
	LPO6	0.88				
LRE	**LRE1**	0.85	0.82	0.82	0.89	0.65
	LRE3	0.89				
	LRE6	0.84				
MMI	**MMI4**	0.92	0.93	0.93	0.95	0.72
	MMI5	0.95				
	MMI7	0.93				
PPE	**PPE2**	0.93	0.92	0.93	0.96	0.77
	PPE3	0.92				
	PPE4	0.94				

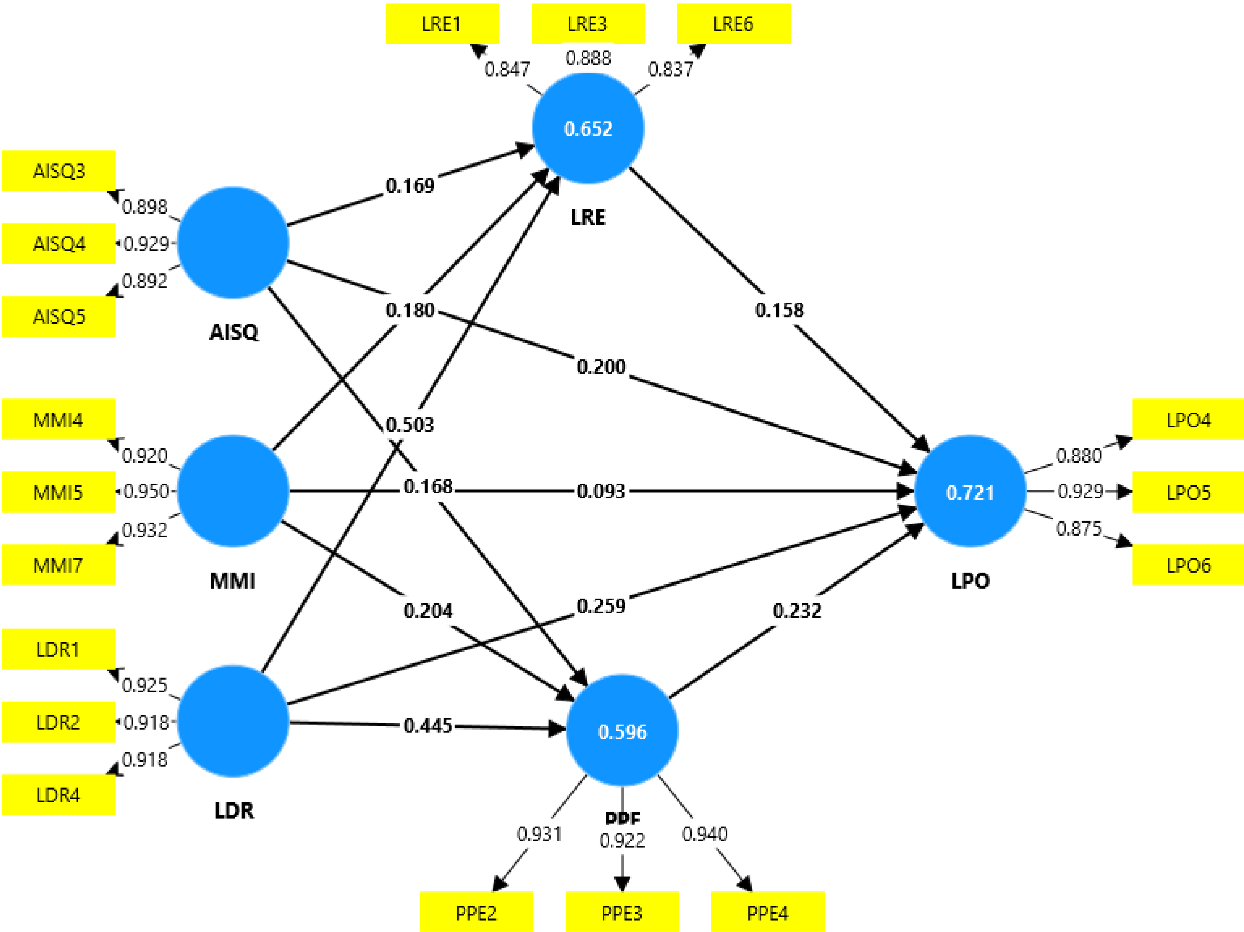
Table 5

The Inter-item Correlations

	AISQ	ABSD	AEPR	LDR	EAA	OPE
AISQ	**0.86**					
ABSD	0.83	**0.85**				
AEPR	0.81	0.84	**0.74**			
LDR	0.81	0.77	0.66	**0.81**		
EAA	0.82	0.81	0.73	0.78	**0.85**	
OPE	0.78	0.84	0.72	0.72	0.84	**0.88**

Figure 2

The Path Model



5.2 The Structural Model

The hypotheses testing reveal that LDR is the most influential predictor, significantly enhancing LPO ($\beta = 0.442$, $t = 4.423$, $p = 0.008$) directly and also through its strong effects on LRE ($\beta = 0.503$, $t = 5.392$, $p = 0.000$) and PPE ($\beta = 0.445$, $t = 4.504$, $p = 0.000$). AISQ also positively impacts LPO ($\beta = 0.266$, $t = 3.613$, $p = 0.003$) and LRE ($\beta = 0.169$, $t = 2.378$, $p = 0.017$), though its effect on PPE is not statistically significant ($\beta = 0.168$, $t = 1.887$, $p = 0.059$). Both LRE ($\beta = 0.158$, $t = 1.975$, $p = 0.048$) and PPE ($\beta = 0.232$, $t = 2.428$, $p = 0.015$) significantly contribute to LPO, supporting their mediating roles. However, MMI does not significantly affect LPO ($\beta = 0.168$, $t = 1.343$, $p = 0.437$), LRE ($\beta = 0.180$, $t = 1.832$, $p = 0.067$), or PPE ($\beta = 0.204$, $t = 1.635$, $p = 0.102$), suggesting that interactivity alone is insufficient without supportive learner or system factors.

The mediation analysis indicates that only one indirect effect pathway is statistically supported: LDR → PPE → LPO ($\beta = 0.103$, $t = 1.964$, $p = 0.050$), highlighting the importance of digital readiness in enhancing personalized learning through perceived personalization. All other mediation paths, including those involving MMI and AISQ through either PPE or LRE, were not statistically significant ($p > 0.05$), suggesting that these predictors do not influence LPO indirectly via the mediators in the current model. This reinforces the unique mediating role of PPE specifically in the context of digital readiness.

Table 6

The t-Statistic

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics**	**P values**	**Hypothesis**
AISQ -> LPO	0.266	0.265	0.074	3.613	0.003	**Supported**
AISQ -> LRE	0.169	0.173	0.071	2.378	0.017	**Supported**
AISQ -> PPE	0.168	0.165	0.089	1.887	0.059	Not supported
LDR -> LPO	0.442	0.448	0.100	4.423	0.008	**Supported**
LDR -> LRE	0.503	0.503	0.093	5.392	0.000	**Supported**
LDR -> PPE	0.445	0.443	0.099	4.504	0.000	**Supported**
LRE -> LPO	0.158	0.157	0.080	1.975	0.048	**Supported**
MMI -> LPO	0.168	0.164	0.125	1.343	0.437	Not supported
MMI -> LRE	0.180	0.178	0.098	1.832	0.067	Not supported
MMI -> PPE	0.204	0.209	0.125	1.635	0.102	Not supported
PPE -> LPO	0.232	0.226	0.096	2.428	0.015	**Supported**

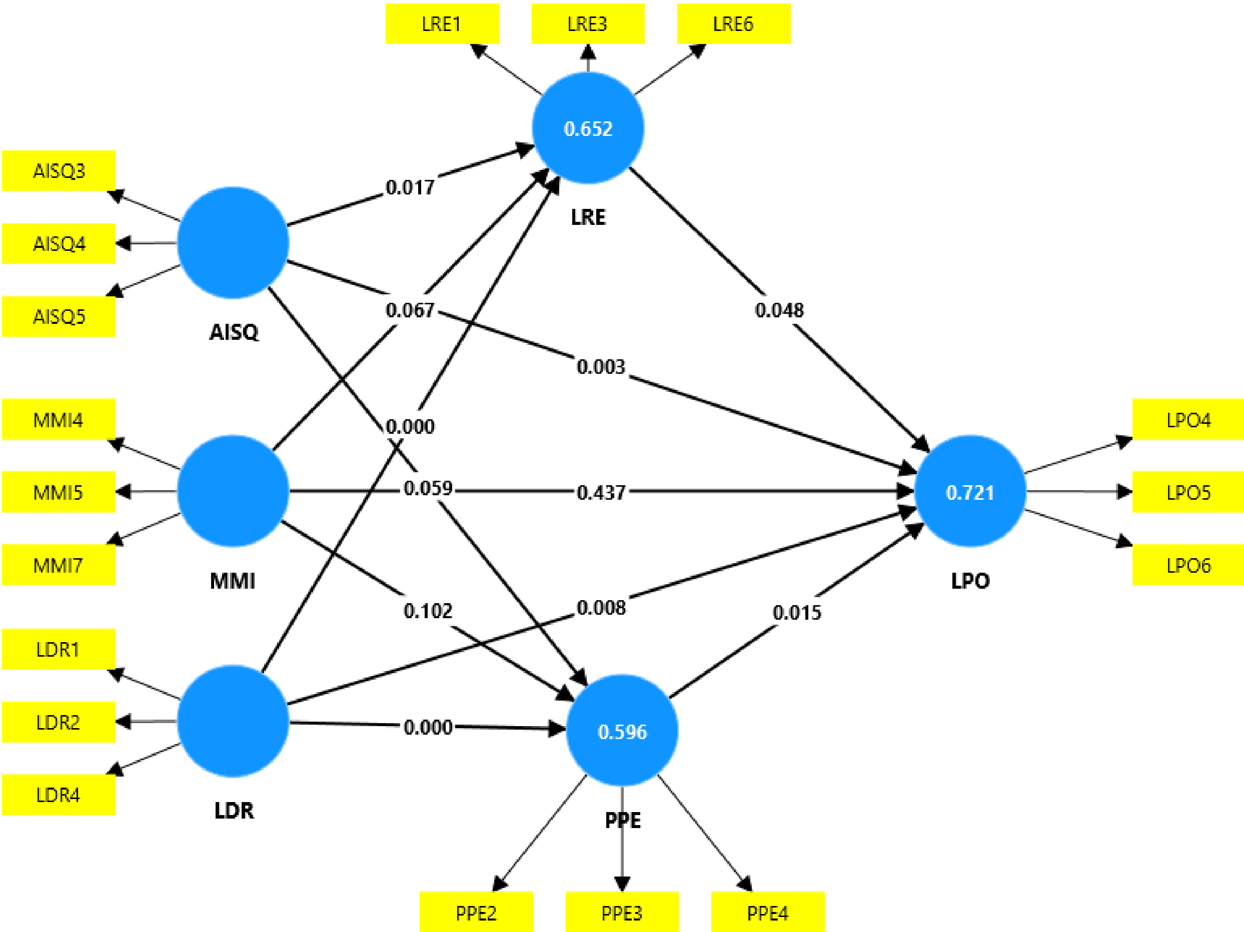
Table 7

The t-Statistic – Indirect Relationships

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics**	**P values**	**Hypothesis**
MMI -> PPE -> LPO	0.047	0.042	0.030	1.568	0.117	Not supported
MMI -> LRE -> LPO	0.028	0.027	0.021	1.374	0.169	Not supported
AISQ -> PPE -> LPO	0.039	0.040	0.031	1.266	0.206	Not supported
LDR -> PPE -> LPO	0.103	0.102	0.053	1.964	0.050	**Supported**
AISQ -> LRE -> LPO	0.027	0.028	0.021	1.284	0.199	Not supported
LDR -> LRE -> LPO	0.079	0.079	0.043	1.826	0.068	Not supported

Figure 3

The Structural Model



6. Discussions

This study provides valuable empirical evidence regarding the mechanisms underlying personalized learning path optimization in AI-enhanced educational environments. The results demonstrate that Learner Digital Readiness serves as the most critical determinant of learning path optimization, exhibiting strong direct effects and functioning as a key antecedent to both engagement and perceived personalization. These findings corroborate existing theoretical perspectives that position digital competence as a fundamental enabler in technology-mediated learning (Hung et al., 2010; Wei, 2024), while extending this understanding by revealing the specific pathways through which digital readiness operates. The particularly robust mediation through Perceived Personalization Effectiveness suggests that digitally prepared learners are not only more adept at using adaptive systems but are also more likely to recognize and benefit from personalized features.

The significant role of AI System Quality in directly influencing learning outcomes aligns with prior research emphasizing the importance of technical reliability in educational technologies (Chen et al., 2020; Alshahrani et al., 2019). However, the non-significant relationship with perceived personalization offers an important nuance, indicating that system performance alone may not suffice to create a sense of individualized learning. This distinction underscores the need to differentiate between technical personalization capabilities and learners' subjective experience of personalization, a critical consideration for system designers.

The confirmed importance of both engagement and perceived personalization as mediators supports established learning theories while providing new insights into their relative contributions

(Fredricks et al., 2004; Wang et al., 2022). The non-significant findings regarding Multimedia Interactivity, while surprising in light of conventional multimedia learning principles (Mayer, 2005; Zhang et al., 2006), suggest that interactive features may require stronger integration with adaptive algorithms and learner profiles to realize their full potential in personalized learning contexts.

7. Theoretical Implications

This study advances theoretical understanding of AI-enhanced personalized learning through three key contributions. First, it integrates three foundational frameworks TAM, CLT, and CLT into a unified model that explains how technological, cognitive, and pedagogical factors jointly influence learning path optimization. This synthesis addresses a critical gap in the literature, where these perspectives have typically been examined in isolation, by demonstrating their interconnected roles in personalized learning environments.

The findings particularly highlight LDR as a pivotal construct that operationalizes all three theoretical perspectives. LDR enhances technology adoption, manages cognitive load, and enables constructive engagement, revealing its multifaceted role as both a prerequisite and catalyst for effective personalization. This challenges conventional views of learner characteristics as mere background variables, instead positioning them as active mediators between system design and learning outcomes.

Notably, the non-significant findings for MMI prompt important theoretical reconsiderations. While MMI has demonstrated value in traditional e-learning, its limited impact in this AI-driven context suggests that conventional interactivity metrics may not adequately capture meaningful engagement in adaptive environments. This insight calls for new conceptualizations of interactivity that emphasize dynamic, learner-responsive interactions over static click-based measures

Key Theoretical Insights:

1. Digital readiness transforms from a baseline requirement to an active enhancer of personalized learning
2. System personalization must be both technically sound and perceptually meaningful to learners
3. Interactivity effects are contingent on integration with adaptive logic and learner readiness

These contributions collectively advance research toward more holistic models of AI-enhanced learning that account for the complex interplay between system capabilities, instructional design, and learner characteristics.

8. Practical Implications

These findings of this research offer several actionable insights for educational practice which can be mainly grouped under three headings.

8.1 Digital Competency Development

Digital Competency Development should be prioritized as a foundational element for successful implementation of adaptive learning systems. The finding that LDR is the strongest predictor of learning path optimization carries significant implications for educational practice. Rather than treating digital literacy as an incidental skill, institutions implementing AI-driven adaptive learning systems may strategically prioritize comprehensive digital competency development as a fundamental prerequisite. This goes beyond basic technical training and it requires cultivating the following aspects.

8.1.1 Systematic Digital Readiness Programs

To enhance the digital presence in learning, particularly in AI-driven adaptive environments, it is essential to design structured curricula that intentionally develop students' technical, cognitive, and adaptive digital competencies. Technical skills such as platform navigation, troubleshooting common system errors, and managing device settings form the foundational layer of digital readiness, enabling learners to access and interact with digital learning systems with confidence. Cognitive skills, including the ability to evaluate the credibility of digital resources, interpret adaptive feedback, and differentiate between system-generated suggestions and instructor-provided content, are critical for informed learning decision-making. Furthermore, adaptive skills such as self-regulated learning, goal-setting, time management, and reflection in AI-supported environments empower students to take ownership of their learning paths, respond constructively to personalization, and maintain sustained engagement. Integrating these skill domains within the curriculum ensures that learners are not merely passive recipients of technology but are prepared to actively engage, adapt, and thrive in data-driven learning ecosystems. This multidimensional approach to digital literacy development is particularly vital in Basic Education contexts, where digital maturity varies and institutional support is still evolving.

Embedded training modules within courses using adaptive systems ensure digital skills are developed contextually, allowing learners to immediately apply new competencies within authentic learning scenarios. These modules should be designed as just-in-time microlearning units that align with the system's adaptive logic, for example, teaching learners how to interpret personalized dashboards when they first encounter analytics features. By scaffolding digital skill development alongside content mastery, institutions can create a seamless loop where improved digital literacy enhances adaptive system use, which in turn reinforces both subject learning and technological fluency.

8.1.2 Teacher Capacity Building

Effective implementation of adaptive learning systems requires comprehensive professional development that empowers educators to become skilled facilitators of technology-mediated learning. These programs should transcend basic operational training and instead emphasize: (1) strategic interpretation of learning analytics to inform instructional decisions, (2) development of metacognitive strategies for guiding students through personalized content, and (3) cultivation of digital pedagogies that leverage adaptive features to enhance rather than replace human teaching.

When educators achieve mastery in these areas, they perform multiple critical functions: they demonstrate authentic use of adaptive tools, establish productive learning routines, and scaffold students' transition to more autonomous learning. Particularly valuable is their ability to model reflective engagement with AI-generated feedback showing students how to interpret recommendations, adjust strategies, and connect system insights to broader learning goals. This modelling is crucial for developing students' self-regulation skills within technology-rich environments.

Ultimately, such professional learning initiatives serve as catalysts for institutional change, transforming adaptive systems from isolated tools into integral components of a responsive, data-informed educational ecosystem. The investment yields compounding returns as digitally fluent educators create classrooms where both the technical and pedagogical potential of AI-enhanced learning can be fully realized.

Effective implementation of adaptive learning systems requires educators who can identify and address students' digital skill gaps. Training should help teachers distinguish between technical struggles (like navigation errors or unused features) and academic challenges, using tools such as: classroom observation protocols, platform analytics dashboards, and Brief competency assessments. Armed with these insights, instructors can provide: targeted just-in-time assistance, curated skill-building resources, and adjusted instructional scaffolding. This proactive approach is especially valuable in diverse settings like Kuwait's Basic Education Colleges, where varying technology exposure among students makes continuous digital support essential for equitable learning.

8.2 Phased Implementation Approach

The successful integration of AI-driven adaptive learning systems necessitates careful evaluation of students' existing digital competencies prior to implementation. Comprehensive pre-assessment of skills ranging from basic technical operations to advanced self-regulated learning behaviors provides critical data for identifying population-level readiness and individual learning needs. These diagnostic measures enable institutions to develop precisely targeted support structures, whether through differentiated workshops, embedded skill-building modules, or adjusted implementation timelines that address identified gaps while leveraging existing strengths.

Such preparatory work serves multiple pedagogical purposes: it establishes equitable access conditions by ensuring all learners possess baseline operational fluency, informs resource allocation decisions, and allows for the alignment of system design with the cohort's actual digital learning profile. Perhaps most significantly, this proactive approach transforms digital readiness from a potential barrier to an enabler of personalized learning, creating conditions where both the technological infrastructure and learner capabilities can mutually reinforce educational effectiveness.

The implementation of AI-driven adaptive learning systems requires carefully structured digital literacy programs that evolve with learners' growing competencies. Initial workshops should establish essential operational skills—platform navigation, content access, and basic interaction protocols—to create an inclusive foundation for all users. As learners progress, intermediate sessions can introduce more sophisticated engagement with adaptive features, emphasizing the interpretation of system-generated feedback and participation in algorithm-mediated activities. The most advanced training should cultivate strategic, self-directed learning behaviors, enabling students to synthesize AI analytics with personal learning objectives and intentionally shape their educational trajectories.

This phased approach serves two critical functions: it accommodates varying entry-level competencies while systematically building the specific skill sets needed to fully leverage adaptive personalization. By aligning workshop content with both system capabilities and pedagogical goals, institutions can transform digital literacy from a basic prerequisite into an ongoing enabler of AI-mediated learning success. The ultimate objective is to develop learners who are not merely proficient platform users, but sophisticated partners in the personalized education process.

8.2.1 Design Considerations for System Developers

Effective implementation of AI-driven learning platforms necessitates intelligent onboarding mechanisms that accommodate varying levels of digital literacy. Built-in competency screeners, deployed during initial system access, can evaluate fundamental technological proficiencies and prior experience with adaptive learning tools. These diagnostic instruments enable the platform to generate individualized orientation pathways through machine learning algorithms.

Subsequent adaptive tutorials dynamically adjust their scaffolding based on diagnostic results, creating differentiated learning curves. For instance, users demonstrating limited digital fluency receive granular, interactive guidance for core functionalities, while proficient users are directed toward advanced customization features. This stratified approach: minimizes cognitive load during critical first exposures, accelerates platform mastery through targeted skill-building, reduces instructor burden for basic technical support, and promotes equitable access across heterogeneous user populations.

8.2.2 Supporting Digital Readiness and Personalization

The pedagogical significance of such onboarding systems lies in their capacity to transform initial interactions into authentic personalized learning experiences. By anticipating and addressing competency gaps at the entry point, platforms establish stronger foundations for sustained engagement and independent learning behaviors. This aligns with contemporary principles of universal design for learning while addressing practical challenges of digital inclusion in diverse educational contexts.

To build learner trust and promote meaningful engagement with AI-driven adaptive systems, it is crucial to design a transparent and intuitive user interface (UI) and user experience (UX) that clearly communicates the system’s capabilities and personalization logic. Many students may engage with adaptive platforms without fully understanding how or why certain content is recommended or why learning paths are adjusted. By integrating visual indicators, tooltips, progress trackers, and explanation prompts, the system can make its decision-making process more interpretable and learner-friendly. For instance, showing messages like “This activity was suggested based on your last quiz performance” or “You’re on a faster learning track due to consistent progress” helps demystify the AI’s adaptive function. Furthermore, dashboard visualizations that explain how learners are progressing, what adjustments have been made, and what future steps are suggested empower students to take ownership of their learning. A transparent UI/UX not only fosters learner autonomy and self-regulation but also enhances the perceived credibility of the system, particularly important in educational contexts like Basic Education Colleges in Kuwait, where learners may be less familiar with complex AI processes.

This proactive approach recognizes that even the most sophisticated adaptive system will underperform if learners lack the digital fluency to engage with it meaningfully. By treating digital readiness as an institutional priority rather than an assumed prerequisite, schools can ensure their investments in AI-driven personalization yield equitable, scalable benefits.
A university deploying an adaptive learning platform could: Administer a validated digital readiness survey during orientation, and assign targeted micro-courses (e.g., "Interpreting AI Feedback") based on results. Track reduced support requests/improved outcomes as indicators of program efficacy. This evidence-based strategy aligns with UNESCO's Digital Competency Framework (Bitegeko et al., 2024) while addressing the study's key finding that LDR enables learners to both use and benefit from adaptive personalization features.

9. Conclusion

This study provides critical insights into the implementation of AI-driven adaptive learning systems by examining their impact on personalized learning path optimization within Kuwait's Basic Education Colleges. Our findings reveal that learner digital readiness serves as the cornerstone for successful adoption and utilization of these systems, demonstrating significant direct and mediated effects on learning outcomes. The research establishes that while AI system quality and perceived personalization effectiveness contribute meaningfully to learning optimization, conventional multimedia interactivity alone proves insufficient without deeper integration with adaptive logic and learner profiles.

The theoretical implications are threefold. First, we contribute to the advancement of an integrated framework that bridges technology acceptance, cognitive load, and constructivist learning theories. Second, we reposition digital readiness as an active mediator rather than a passive prerequisite in personalized learning. Third, we challenge prevailing assumptions about multimedia interactivity by demonstrating its limited standalone value in adaptive environments. These contributions call for new conceptualizations of interactivity that emphasize dynamic, learner-responsive designs.

From a practical perspective, our results underscore the necessity of: (1) comprehensive digital readiness initiatives that evolve with learner needs; (2) educator professional development focused on AI system mediation; (3) transparent interface designs that build learner trust, and (4) adaptive onboarding processes that accommodate diverse skill levels. While the study's cross-sectional design and contextual focus present limitations, they also create opportunities for future research. Longitudinal studies tracking digital competency development, investigations into cultural dimensions of AI acceptance, and qualitative explorations of learner perceptions would further enrich our understanding.

As educational institutions worldwide embrace AI-enhanced learning, this research provides an evidence-based foundation for implementation strategies that prioritize both technological sophistication and human-centered design. The findings ultimately advocate for an educational future where adaptive systems and learner development grow in tandem, creating more equitable, engaging, and effective personalized learning experiences. The role of AI-driven adaptive multimedia systems on personalized learning paths has been explored quantitatively through this research. Future researchers may conduct qualitative interviews to gain insightful and stimulating experiences from students regarding these technologies.

10. Co-Author Contribution

This is a single author paper and hence this section is not applicable.

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