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Adaptive Dual-AI Systems in E-Learning: A Dual-Path Analysis of LLMs and Hybrid AI Adoption Across Generations

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Abstract

Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)-based hybrid AI systems are increasingly transforming higher education, yet it remains unclear whether they are adopted through similar or distinct technology adoption pathways. This study compares the adoption of these two AI paradigms among postgraduate students using the Unified Theory of Acceptance and Use of Technology (UTAUT). It proposes the Adaptive Dual-AI Model (ADAM), which extends UTAUT by examining architecture-sensitive AI adoption within a unified framework. The model incorporates Technology Readiness (TR) and AI Awareness (AIA) as mediating variables and generational differences (Gen Z and Gen Y) as moderating factors. Data were collected from 639 postgraduate students enrolled in Saudi universities, of which 619 valid responses were retained after data screening. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to evaluate the proposed model. The results indicate that the two AI paradigms follow distinct technology adoption pathways. Behavioural intention toward standalone LLMs was primarily associated with Performance Expectancy (PE) and Effort Expectancy (EE), whereas the adoption of RAG-based hybrid AI systems was more strongly associated with indirect relationships involving Technology Readiness and AI Awareness. Multi-group analysis further revealed that Gen Z learners exhibited stronger associations with LLM adoption, whereas Gen Y learners demonstrated stronger relationships involving RAG-based hybrid AI systems. These findings support the proposed architecture-sensitive perspective of ADAM, suggesting that differences in AI architecture are associated with distinct technology adoption patterns. From a practical perspective, the findings provide guidance for higher education institutions in selecting complementary AI technologies according to learning objectives, learner characteristics, and evidence requirements. More broadly, the study contributes to technology adoption research by extending UTAUT to heterogeneous AI ecosystems and offers practical insights for designing adaptive, personalised, and evidence-aware learning environments.



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Keywords: artificial intelligence (AI); large language models (LLMs); hybrid AI systems; adaptive e-learning; generational differences; adaptive dual-AI model (ADAM); postgraduate students; PLS-SEM; personalised learning; intelligent tutoring systems; evidence-based AI

1. Introduction

The rapid advancement of artificial intelligence (AI) has transformed higher education by changing how learners access, evaluate, and apply academic knowledge. Recent developments in generative AI have expanded opportunities for personalised learning, adaptive

educational support, and intelligent knowledge interaction, thereby reshaping teaching, learning, and research practices [1–4].

Among these developments, Large Language Models (LLMs) have become widely adopted for academic writing, summarisation, explanation, and conversational learning. However, because standalone LLMs generate responses primarily from internal model knowledge, concerns remain regarding hallucination, transparency, and the verifiability of generated information [5–10]. To address these limitations, Retrieval-Augmented Generation (RAG)-based hybrid AI systems integrate language generation with external knowledge retrieval, enabling evidence-grounded responses supported by source attribution and information verification [11–15].

Despite the growing adoption of AI in higher education, several important research gaps remain. First, previous studies have largely examined standalone LLMs or traditional information retrieval systems separately, with limited attention to RAG-based hybrid AI systems as a distinct educational technology [16]. Second, few studies have compared these complementary AI paradigms within a unified technology adoption framework [17]. Third, existing technology adoption models, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT), do not fully explain whether different AI architectures are associated with distinct technology adoption pathways. In addition, relatively little attention has been given to the mediating roles of Technology Readiness (TR) and AI Awareness (AIA) or the moderating influence of generational differences in explaining AI adoption within adaptive learning environments [18–20].

To address these gaps, this study develops a dual-path framework for comparing the adoption of standalone LLMs and RAG-based hybrid AI systems in higher education. Building on UTAUT, the proposed framework incorporates Technology Readiness and AI Awareness as mediating mechanisms and generational differences (Gen Z and Gen Y) as moderating factors. Rather than assuming that all AI technologies are adopted through a common process, the framework proposes that differences in AI architecture are associated with distinct technology adoption pathways, particularly between efficiency-oriented and evidence-oriented educational AI systems. The following research questions guide the study:

RQ1: How do LLMs and RAG-based hybrid AI systems differ in their adoption mechanisms within adaptive e-learning environments?

RQ2: To what extent do Performance Expectancy (PE) and Effort Expectancy (EE) influence Behavioural Intention (BI) toward LLMs and RAG-based hybrid AI systems?

RQ3: What roles do Technology Readiness (TR) and AI Awareness (AIA) play in the indirect relationships between the UTAUT constructs and behavioural intention toward LLMs and RAG-based hybrid AI systems?

RQ4: Which AI paradigm demonstrates greater predictive capability for Actual Usage Behaviour (AUB) among postgraduate students?

RQ5: How do generational differences between Gen Z and Gen Y influence the adoption pathways of LLMs and RAG-based hybrid AI systems?

RQ6: How can the proposed Adaptive Dual-AI Model (ADAM) support adaptive, evidence-aware e-learning environments?

To address these questions, this study proposes the Adaptive Dual-AI Model (ADAM) as a conceptual framework for examining technology adoption across two complementary AI paradigms. Rather than replacing UTAUT, ADAM extends it by introducing an architecture-sensitive perspective on AI adoption. Specifically, the framework proposes that standalone LLMs are primarily associated with efficiency-oriented adoption pathways, whereas RAG-based hybrid AI systems are more strongly associated with evidence-oriented adoption pathways in which Technology Readiness, AI Awareness, and information cred-

ibility assume greater importance. ADAM further proposes that the relative strength of these pathways varies across generations, reflecting differences in digital experience and AI use. Accordingly, the model should be viewed as a complementary conceptual framework that distinguishes between heterogeneous AI adoption pathways while remaining grounded in established technology acceptance theory [11,15,19,20].

This study makes several theoretical and practical contributions. Theoretically, it extends UTAUT by introducing an architecture-sensitive perspective that integrates Technology Readiness, AI Awareness, and generational moderation within a unified framework for comparing complementary AI paradigms [21]. Practically, the findings provide guidance for higher education institutions, educators, and AI system designers seeking to develop adaptive, personalised, and evidence-aware learning environments. The proposed ADAM framework offers practical insights into selecting appropriate AI technologies according to learning objectives, learner characteristics, and evidence requirements while promoting the responsible use of artificial intelligence [22].

2. Literature Review and Research Hypotheses

2.1. AI-Driven E-Learning Systems: LLMs and Hybrid AI Systems

Artificial intelligence (AI) has become a key enabler of adaptive e-learning by supporting personalised instruction, intelligent tutoring, and interactive knowledge construction [23]. Earlier digital learning environments were primarily based on information retrieval (IR), requiring learners to search, evaluate, and synthesise information from multiple digital sources [24].

Although these systems improved access to educational resources, they often imposed considerable cognitive demands, particularly on postgraduate students and novice researchers who were required to evaluate the credibility and relevance of retrieved information [25]. Consequently, recent AI developments have shifted educational technologies from information retrieval toward intelligent knowledge generation and adaptive learning support [26].

A major development has been the emergence of Large Language Models (LLMs), which generate coherent, context-aware responses through transformer-based language generation rather than conventional retrieval processes [27,28]. These systems support academic writing, summarisation, explanation, and conversational learning while reducing learners' cognitive effort and improving learning efficiency [29,30].

As a result, most studies examining LLM adoption have focused primarily on usability, perceived usefulness, and productivity outcomes [31]. However, standalone LLMs may generate responses that are not always supported by verifiable evidence, raising concerns regarding hallucination, transparency, academic integrity, and information reliability [32].

To address these limitations, Retrieval-Augmented Generation (RAG) has emerged as an increasingly established AI architecture that combines LLM-based generation with retrieval mechanisms capable of accessing external knowledge repositories during inference [33–35].

Rather than relying solely on parametric knowledge stored during model training, RAG retrieves relevant evidence before generating responses, thereby improving factual consistency, explainability, transparency, and source traceability while reducing hallucinations [31,36,37]. In educational settings, this architecture provides an appropriate foundation for evidence-grounded learning because learners can verify AI-generated responses using retrieved sources and supporting evidence.

Despite these advances, important gaps remain in the AI adoption literature. Most previous studies have examined either standalone LLMs or traditional information retrieval systems independently, with limited attention to RAG-based hybrid AI systems as a distinct

educational technology [38]. Furthermore, existing technology adoption research has largely emphasised usability and performance outcomes without distinguishing between efficiency-oriented interaction associated with standalone LLMs and evidence-oriented interaction associated with retrieval-augmented systems [29–35,39–43].

Consequently, little is known about whether these two AI paradigms follow similar or different adoption mechanisms within adaptive e-learning environments [44,45]. The present study addresses these gaps by comparing standalone LLMs and RAG-based hybrid AI systems within a unified technology adoption framework. Unlike previous studies that examined AI systems as a homogeneous category, this study argues that different AI architectures may encourage different technology adoption pathways.

Specifically, standalone LLMs primarily support rapid knowledge generation and efficiency-oriented interaction, whereas RAG-based hybrid AI systems emphasise evidence-grounded reasoning, source verification, and information credibility. This distinction provides the theoretical foundation for examining whether users adopt these two AI paradigms through different behavioural mechanisms.

The proposed framework builds upon the Unified Theory of Acceptance and Use of Technology (UTAUT), which explains technology adoption through four core determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) [46]. These constructs have consistently predicted behavioural intention across diverse educational technologies and AI-supported learning environments [22,34,46].

Because standalone LLMs and RAG-based hybrid AI systems both support learning through artificial intelligence, the core UTAUT relationships are expected to remain applicable across both paradigms. However, their relative influence may vary according to the characteristics of the underlying AI architecture. Accordingly, Theoretical Proposition 1 (P1) posits that the core UTAUT determinants remain valid predictors of technology adoption across both AI paradigms, although their relative effects may differ between standalone LLMs and RAG-based hybrid AI systems. This proposition is operationalised through the following eight hypotheses:

- H1.** *PE positively influences BI toward LLMs.*
- H2.** *EE positively influences BI toward LLMs.*
- H3.** *SI positively influences BI toward LLMs.*
- H4.** *FC positively influences BI toward LLMs.*
- H5.** *PE positively influences BI toward hybrid AI systems.*
- H6.** *EE positively influences BI toward hybrid AI systems.*
- H7.** *SI positively influences BI toward hybrid AI systems.*
- H8.** *FC positively influences BI toward hybrid AI systems.*

2.2. Cognitive Mediation, Generation Differences, and Adaptive AI Adoption

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains technology adoption through four core determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) [46]. Although these constructs have demonstrated strong explanatory power across a wide range of

educational technologies, adaptive AI systems introduce additional technology evaluation considerations that extend beyond traditional technology acceptance models [47].

In AI-supported learning environments, users evaluate not only system usability but also the credibility, transparency, explainability, and reliability of AI-generated information [48]. Consequently, Technology Readiness (TR) and AI Awareness (AIA) are expected to influence how users translate technology perceptions into behavioural intention [49].

In the present study, Technology Readiness (TR) refers to users' preparedness and confidence in using AI technologies effectively, including their willingness to adopt AI systems and their perceptions of the reliability and credibility of AI-generated outputs [50,51]. This construct is expected to play a particularly important role in RAG-based hybrid AI systems because these systems encourage users to evaluate retrieved evidence, source attribution, and information verification [52,53]. By contrast, standalone LLMs primarily support rapid and intuitive interaction, which may reduce users' reliance on extensive evidence-verification processes during routine learning activities [54].

AI Awareness (AIA) is defined as users' understanding of AI capabilities, limitations, transparency mechanisms, potential risks, and responsible-use considerations. It represents a cognitive evaluation construct rather than an emotional response and should therefore be distinguished from AI anxiety. Learners with higher AI Awareness are expected to evaluate AI-generated content more critically, recognise system limitations, and make more informed decisions regarding the appropriate use of AI in academic settings [13,55].

Previous studies have recognised the importance of Technology Readiness and AI Awareness in AI adoption [22]. However, these constructs have generally been examined either independently or within a single AI paradigm, with limited attention to differences between standalone LLMs and RAG-based hybrid AI systems [15]. Consequently, little is known about whether these cognitive mechanisms operate similarly across different AI architectures. Building on this gap, the present study proposes that Technology Readiness and AI Awareness may exhibit different levels of influence across the two AI paradigms.

Rather than assuming that all AI technologies follow identical adoption processes, the proposed framework suggests that AI architecture may influence how users evaluate and adopt different AI paradigms. Standalone LLMs are expected to be associated primarily with efficiency-oriented evaluations, whereas RAG-based hybrid AI systems may place greater emphasis on evidence-oriented evaluation because of their retrieval and source-verification capabilities [24,26,35].

Within this framework, Technology Readiness (TR) and AI Awareness (AIA) are conceptualised as architecture-dependent mechanisms that help explain how users translate perceptions of usefulness and ease of use into behavioural intention. Rather than serving as additional predictors, these constructs are proposed to account for differences in adoption pathways across the two AI paradigms.

Accordingly, Theoretical Proposition 2 (P2) posits that Technology Readiness and AI Awareness function as complementary mechanisms linking the core UTAUT determinants to behavioural intention, with their relative importance varying according to AI architecture. This proposition is operationalised through the following mediation hypotheses:

H9. *TR mediates the relationship between PE and BI toward LLMs.*

H10. *TR mediates the relationship between PE and BI toward hybrid AI systems.*

H11. *AIA mediates the relationship between EE and BI toward LLMs.*

H12. *AIA mediates the relationship between EE and BI toward hybrid AI systems.*

Finally, behavioural intention is expected to predict actual AI usage across both AI paradigms, consistent with the behavioural continuity proposed by UTAUT. Accordingly, Theoretical Proposition 3 (P3) states that behavioural intention is positively associated with actual AI usage regardless of AI architecture. This proposition is operationalised through the following hypotheses:

H13. *BI toward LLMs positively influences AUB.*

H14. *BI toward hybrid AI systems positively influences AUB.*

The present study also examines whether generational differences moderate the proposed adoption pathways. Generational cohort theory suggests that individuals who developed their technological habits under different social and digital conditions may differ in their expectations of usefulness, ease of use, credibility, and information verification [17]. Gen Z learners have generally grown up with mobile technologies, social media, and AI-supported digital environments.

Consequently, they tend to value immediacy, intuitive interaction, automation, and task efficiency when adopting emerging technologies. These characteristics suggest that Performance Expectancy and Effort Expectancy may exert stronger influences on behavioural intention toward standalone LLMs among Gen Z users [29].

By comparison, Gen Y learners experienced the transition from conventional digital information systems to contemporary generative AI technologies during their academic and professional development. Previous studies suggest that these users place greater emphasis on structured information processing, source credibility, transparency, and evidence verification when evaluating emerging technologies [30].

Such characteristics are particularly relevant to RAG-based hybrid AI systems, which require users to assess retrieved evidence, citations, and external knowledge sources in addition to generated responses. Consequently, Performance Expectancy, Effort Expectancy, and Technology Readiness are expected to exert stronger influences on behavioural intention toward hybrid AI systems among Gen Y users.

Generational differences may also influence the extent to which behavioural intention translates into actual AI use. Gen Z learners generally interact more frequently with conversational and automated digital technologies and may therefore convert behavioural intention into actual LLM use more readily.

Conversely, Gen Y learners may require greater confidence in information credibility and technological readiness before integrating RAG-based hybrid AI systems into sustained learning and research practices [18,22]. These theoretical arguments provide the basis for examining generation as a moderator of the proposed relationships.

Rather than proposing separate technology acceptance theories for Gen Z and Gen Y, the proposed framework conceptualises generation as a contextual factor that influences the relative strength of the AI adoption pathways. Differences in digital experience are expected to shape the importance of the proposed relationships without altering the underlying UTAUT-based theoretical framework. Accordingly, Theoretical Proposition 4 (P4) posits that generational differences moderate the relative influence of the architecture-sensitive adoption pathways proposed by ADAM, rather than changing the technology acceptance model itself. This proposition is operationalised through the following moderation hypotheses:

H15. *The effect of PE on BI toward LLMs is stronger for Gen Z than for Gen Y.*

H16. *The effect of EE on BI toward LLMs is stronger for Gen Z than for Gen Y.*

H17. *The effect of PE on BI toward hybrid AI systems is stronger for Gen Y than for Gen Z.*

H18. *The effect of EE on BI toward hybrid AI systems is stronger for Gen Y than for Gen Z.*

H19. *The positive relationship between TR and BI toward hybrid AI systems is stronger for Gen Y than for Gen Z.*

H20. *The effect of BI on AUB is stronger for LLMs among Gen Z users.*

2.3. ADAM Theoretical Foundation

The Adaptive Dual-AI Model (ADAM) was developed to address an important limitation of existing technology acceptance models. Conventional UTAUT-based frameworks generally assume that users evaluate a single technology using a common set of determinants, regardless of differences in technological architecture [31]. However, contemporary AI systems differ substantially in the way they generate, retrieve, validate, and present information [22]. Standalone LLMs primarily generate responses from internal model parameters. In contrast, Retrieval-Augmented Generation (RAG)-based hybrid AI systems combine generative capabilities with external knowledge retrieval to produce evidence-grounded and verifiable responses [13]. These architectural differences suggest that users may evaluate and adopt different AI paradigms through different technology adoption pathways.

Accordingly, ADAM proposes a complementary perspective that builds upon UTAUT by distinguishing between two AI adoption pathways. The first pathway is associated with standalone LLMs and reflects efficiency-oriented interaction, in which users primarily evaluate usefulness, ease of use, and rapid knowledge generation. The second pathway is associated with RAG-based hybrid AI systems. It reflects evidence-oriented interaction, in which users place greater emphasis on information credibility, transparency, source verification, and responsible AI use. Within this framework, Technology Readiness (TR) and AI Awareness (AIA) are expected to play a more prominent role in the adoption of hybrid AI systems than in the adoption of standalone LLMs [24–26].

A second assumption underlying ADAM is that technology adoption may vary across generations. Drawing on generational cohort theory, the model proposes that differences in digital experience, learning preferences, and AI interaction patterns influence how users evaluate alternative AI paradigms. Consequently, the relationships among the UTAUT constructs, Technology Readiness, AI Awareness, Behavioural Intention, and Actual Usage Behaviour may differ between Gen Z and Gen Y learners. Rather than introducing a new technology acceptance theory, ADAM should be viewed as a conceptual framework that integrates dual AI paradigms, architecture-dependent adoption mechanisms, and generational moderation within adaptive AI-supported learning environments [10].

Based on the preceding literature review, the proposed research framework is organised around six theoretical propositions (P1–P6), each corresponding to one of the study's six research questions. Although the empirical model tests twenty statistical hypotheses, these hypotheses represent operationalisations of the six broader propositions rather than independent theoretical claims. Each proposition defines a distinct dimension of AI adoption within the Adaptive Dual-AI Model (ADAM), while the associated hypotheses specify the structural relationships required for empirical evaluation using PLS-SEM.

Accordingly, the theoretical propositions provide the conceptual foundation of the model, whereas the hypotheses operationalise these propositions for statistical testing. Table 1 summarises the alignment between the research questions, theoretical propositions, operational hypotheses, statistical analyses, and expected outcomes, thereby ensuring a clear distinction between theory development and empirical validation.

Table 1. Conceptual Alignment Between Theoretical Propositions, Research Questions, Hypotheses, and Statistical Analyses.

Theoretical Proposition	Research Question	Theoretical Foundation	Operational Hypotheses	Statistical Analysis	Expected Outcome
P1. Direct UTAUT Effects	RQ1	Unified Theory of Acceptance and Use of Technology (UTAUT): Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)	H1–H8	PLS-SEM Structural Model (Path coefficients, β , t , p , f^2)	Examine the direct effects of UTAUT constructs on behavioural intention toward LLMs and RAG-based hybrid AI systems.
P2. Mediated AI Adoption	RQ2	Technology Readiness Theory, AI Awareness, and Mediation Theory	H9–H12	Bootstrapping Mediation Analysis (Indirect Effects)	Examine whether Technology Readiness and AI Awareness are associated with the indirect relationships underlying AI adoption.
P3. Behavioural Continuity	RQ3	UTAUT Behavioural Intention–Usage Relationship	H13–H14	Structural Model Assessment	Evaluate the relationship between behavioural intention and actual AI usage behaviour.
P4. Generational Moderation	RQ4	Generational Cohort Theory; Multi-Group Analysis (MGA)	H15–H20	MICOM Measurement Invariance Assessment; PLS-MGA	Compare structural relationships between Gen Z and Gen Y and identify differences in the proposed adoption pathways.
P5. Predictive Performance	RQ5	Predictive Assessment in PLS-SEM	—	R^2 , Adjusted R^2 , Q^2 Predictive Relevance, Effect Sizes (f^2), and Model Fit Indices	Compare the explanatory and predictive performance of the LLM and RAG-based hybrid AI adoption models.
P6. Adaptive AI Contribution	RQ6	Adaptive Learning Theory, Deep Reinforcement Learning, and AI-Supported Personalisation	—	DRL Optimisation Analysis, Comparative Performance Evaluation, and Discussion of ADAM	Illustrate the potential contribution of ADAM in supporting adaptive, personalised, and evidence-aware AI learning environments.

3. Materials and Methods

3.1. Population and Research Sample

Participants were recruited from public and private universities in the Kingdom of Saudi Arabia, where artificial intelligence (AI) and adaptive e-learning technologies are increasingly integrated into teaching, learning, and research. The study focused on postgraduate students from Gen Y (1981–1996) and Gen Z (1997–2012), as these learners frequently use large language models (LLMs) and Retrieval-Augmented Generation (RAG)-based hybrid AI systems for literature review, academic writing, knowledge synthesis, and information verification. This population therefore provided an appropriate context for examining AI adoption across different AI paradigms.

A non-probability, voluntary-response sampling strategy was adopted because of institutional access constraints. The questionnaire was distributed through official academic

communication channels and postgraduate student networks across participating universities. Data were collected over six months (April–October 2025) using a cross-sectional survey design, with each participant completing the questionnaire once.

A total of 639 questionnaires were received. Following data screening, including the removal of incomplete questionnaires, substantial missing data, and inconsistent response patterns, 619 valid responses were retained for analysis. Missing values were minimal and handled using listwise deletion. Examination of the excluded questionnaires revealed no evidence of systematic clustering by demographic characteristics or response patterns, indicating that the excluded cases were broadly distributed across the sample and that listwise deletion was unlikely to introduce meaningful systematic bias.

The final sample included participants from both generational groups and reflected the multicultural composition of Saudi higher education, including respondents from Saudi Arabia, Egypt, Jordan, Yemen, Syria, India, the Philippines, Pakistan, and Bangladesh. This diversity enhances the contextual relevance of the findings for AI-supported multicultural learning environments.

The final analytical sample provided adequate statistical power to estimate the proposed structural model, including mediation, measurement invariance, and multi-group analyses. Nevertheless, because the study employed a cross-sectional design and voluntary-response sampling, the findings should be interpreted as statistical associations rather than causal relationships, and their generalisability may be limited to postgraduate students in Saudi higher education.

3.2. Data Collection and Instrument Development

Data were collected using a structured online questionnaire administered once to each participant during the study period. Participation was voluntary and anonymous. The questionnaire comprised three sections: (i) demographic information, including generational group, nationality, and academic background; (ii) an informed consent statement describing the study objectives, confidentiality procedures, and ethical considerations; and (iii) measurement items assessing all study constructs. Responses were recorded using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Measurement items were adapted from previously validated studies on technology acceptance, artificial intelligence, and educational technology. Separate scales measured Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioural Intention (BI), Technology Readiness (TR), AI Awareness (AIA), and Actual Usage Behaviour (AUB) for both standalone LLMs and Retrieval-Augmented Generation (RAG)-based hybrid AI systems [11,15,18,22–24,31–35,39,46–49,56,57]. The complete measurement constructs, example items, scale anchors, and literature sources are presented in Table 2.

Because the distinction between standalone LLMs and RAG-based hybrid AI systems has become increasingly blurred in commercial applications, participants were provided with operational definitions and illustrative examples before completing the questionnaire [5]. Standalone LLMs were defined as AI systems that primarily generate responses using internal language models and conversational reasoning (e.g., ChatGPT (OpenAI, web version based on GPT-4o, accessed March 2026), Claude (Anthropic Claude 3.7 Sonnet, web version), and Gemini (Google Gemini 2.5 Pro, web version) in their standard conversational modes) [10]. In contrast, hybrid AI systems were defined as retrieval-augmented generation (RAG)-based systems that integrate language generation with external information retrieval, semantic search, source citation, or evidence-grounding capabilities (e.g., Perplexity AI Professional, web version; Microsoft Copilot, web version; Undermind, web version) [22]. Participants were instructed to evaluate each category according to its dominant mode

of interaction rather than optional features that may overlap across platforms. These operational definitions were refined during pilot testing to ensure consistent interpretation among respondents.

Table 2. Measurement Constructs, Items, Scale Anchors, and Sources.

Construct	Item Codes	Example Item	Scale (Likert)	Source
Performance Expectancy (PE-LLM)	PE1–PE4	Using LLMs improves my learning performance	1–5	[31,34]
Effort Expectancy (EE-LLM)	EE1–EE4	Learning to use LLMs is easy for me	1–5	[32,49]
Social Influence (SI-LLM)	SI1–SI4	People who are important to me encourage the use of LLMs	1–5	[35,48]
Facilitating Conditions (FC-LLM)	FC1–FC4	Resources are available to support LLM use	1–5	[21,54]
Performance Expectancy (PE-HYB)	PEH1–PEH4	Hybrid AI systems improve learning effectiveness	1–5	[52,56]
Effort Expectancy (EE-HYB)	EEH1–EEH4	Hybrid AI systems are easy to use	1–5	[34,53]
Social Influence (SI-HYB)	SIH1–SIH4	Others encourage my use of hybrid AI systems	1–5	[33,44]
Facilitating Conditions (FC-HYB)	FCH1–FCH4	Technical support is available	1–5	[21,54]
Technology Readiness (TR)	TR1–TR4	I feel prepared to use advanced AI tools	1–5	[37,54]
AI Awareness (AIA)	AIA1–AIA4	I understand the capabilities and limitations of AI	1–5	[54,56]
Behavioural Intention (BI-LLM)	BI1–BI4	I intend to continue using LLMs	1–5	[52,55]
Behavioural Intention (BI-HYB)	BIH1–BIH4	I intend to continue using hybrid AI systems	1–5	[28,34]
Actual Usage Behaviour (AUB)	AUB1–AUB4	I regularly use AI systems in my studies	1–5	[49,53]

Technology Readiness (TR) measured learners' preparedness to use AI technologies and their perceptions of the credibility and reliability of AI-generated outputs [25,29,40]. AI Awareness (AIA) assessed participants' understanding of AI capabilities, limitations, transparency, responsible use, and potential risks. Consistent with the theoretical framework, AIA represents a cognitive awareness construct rather than AI-related anxiety. Behavioural Intention (BI) measured participants' willingness to continue using standalone LLMs and RAG-based hybrid AI systems for academic activities. In contrast, Actual Usage Behaviour (AUB) assessed the frequency and extent of AI use in postgraduate learning and research tasks [31–35,39–41,46–48].

To strengthen content validity, the questionnaire was reviewed by bilingual experts in educational technology, artificial intelligence, and higher education research. A pilot study involving postgraduate students evaluated the instrument for readability, clarity, relevance, and the distinction between standalone LLMs and RAG-based hybrid AI systems [33]. A forward–backward translation procedure ensured conceptual equivalence between the Arabic and English versions, and minor wording revisions were introduced to improve clarity and contextual appropriateness [29].

Because all constructs were measured with a single self-report questionnaire administered at a single time point, the potential for common method bias (CMB) was evaluated using two complementary procedures. First, Harman's single-factor test indicated that the first unrotated factor accounted for less than 50% of the total variance, suggesting that no single latent factor dominated the covariance structure [22]. Second, full collinearity variance inflation factors (VIFs) were assessed following the procedure proposed by Kock

(2015) [39]. All VIF values were below the recommended threshold of 3.3, indicating that common method bias was unlikely to have materially influenced the findings.

All constructs were modelled as reflective latent variables. Partial Least Squares Structural Equation Modelling (PLS-SEM) was selected because it is appropriate for analysing complex predictive models involving multiple latent constructs, mediation effects, and multi-group comparisons. The measurement model was evaluated using indicator loadings, Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), outer Variance Inflation Factors (VIFs), cross-loadings, the Fornell–Larcker criterion, and the Heterotrait–Monotrait (HTMT) ratio. Measurement invariance between Gen Z and Gen Y was assessed using the Measurement Invariance of Composite Models (MICOM) procedure before conducting the multi-group analysis.

3.3. Deep Reinforcement Learning (DRL) Optimisation Framework

Data were analysed using SmartPLS 4.1 following current guidelines for Partial Least Squares Structural Equation Modelling (PLS-SEM) reporting and model evaluation [30–35,39–42,57]. The measurement model was assessed using indicator loadings, Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), outer Variance Inflation Factors (VIFs), cross-loadings, the Fornell–Larcker criterion, and the Heterotrait–Monotrait (HTMT) ratio. The structural model was subsequently evaluated using path coefficients (β), coefficients of determination (R^2), predictive relevance (Q^2), effect sizes (f^2), and model fit indices. Statistical significance was determined using a non-parametric bootstrapping procedure with 5000 resamples at a two-tailed significance level of $p < 0.05$ [45].

Mediation analysis examined whether Technology Readiness (TR) and AI Awareness (AIA) were indirectly associated with the relationships between the UTAUT constructs and behavioural intention. Given the cross-sectional design, these mediation results were interpreted as indirect statistical associations consistent with the proposed theoretical framework rather than evidence of causal mediation.

To demonstrate the practical application of the proposed Adaptive Dual-AI Model (ADAM), a Deep Reinforcement Learning (DRL) optimisation framework was implemented as a simulation-based decision-support layer [21]. The optimisation problem was formulated as a Markov Decision Process (MDP), in which the state space represented learners' latent characteristics derived from the validated constructs (PE, EE, SI, FC, TR, AIA, BI, and AUB). The action space consisted of adaptive instructional decisions, including recommending standalone LLMs or Retrieval-Augmented Generation (RAG)-based hybrid AI systems, adjusting the degree of evidence grounding, and personalising learning support according to learner profiles [52,54].

The reward function maximised predicted behavioural intention, actual usage behaviour, and evidence-grounded learning performance while minimising suboptimal AI recommendations. During optimisation, the DRL agent updated its recommendation policy using the validated behavioural relationships estimated by the PLS-SEM model [33]. Consequently, the reported optimisation percentages represent simulation-based improvements relative to a non-adaptive recommendation strategy rather than behavioural outcomes observed from participants [29–58].

Accordingly, the DRL framework should be interpreted as a proof-of-concept decision-support simulation that demonstrates how the validated PLS-SEM relationships can be operationalised within adaptive recommendation systems. It complements the empirical findings by illustrating the practical implementation of ADAM but does not constitute an additional empirical experiment or statistical validation.

4. Results

Table 3 summarises the measurement model results. All indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.776 to 0.902, confirming satisfactory indicator reliability. Mean scores ranged from 3.88 to 4.33, indicating generally positive perceptions of both standalone LLMs and RAG-based hybrid AI systems. Average Variance Extracted (AVE) values ranged from 0.648 to 0.752, exceeding the recommended threshold of 0.50 and demonstrating satisfactory convergent validity. Composite Reliability (CR) values ranged from 0.880 to 0.920, while Cronbach's alpha values ranged from 0.828 to 0.885, confirming strong internal consistency across all constructs.

Table 3. Quality Criteria for Conceptual Model and Indicator Loadings.

Constructs	Indicators	Loading	Mean	AVE	CR	α
Performance Expectancy—LLM (PE-LLM)	PE1	0.884	4.21	0.701	0.903	0.857
	PE2	0.861				
	PE3	0.843				
	PE4	0.812				
Effort Expectancy—LLM (EE-LLM)	EE1	0.872	4.33	0.688	0.897	0.846
	EE2	0.854				
	EE3	0.826				
	EE4	0.798				
Performance Expectancy—Hybrid (PE-HYB)	PEH1	0.861	3.94	0.661	0.886	0.831
	PEH2	0.842				
	PEH3	0.803				
	PEH4	0.781				
Effort Expectancy—Hybrid (EE-HYB)	EEH1	0.854	3.88	0.648	0.880	0.828
	EEH2	0.832				
	EEH3	0.801				
	EEH4	0.776				
Technology Readiness (TR)	TR1	0.891	4.02	0.731	0.909	0.869
	TR2	0.874				
	TR3	0.842				
	TR4	0.821				
AI Awareness (AIA)	AIA1	0.883	3.97	0.714	0.900	0.861
	AIA2	0.861				
	AIA3	0.832				
	AIA4	0.809				
Behavioural Intention—LLM (BI-LLM)	BIL1	0.902	4.28	0.752	0.920	0.885
	BIL2	0.881				
	BIL3	0.854				
	BIL4	0.836				
Behavioural Intention—Hybrid (BI-HYB)	BIH1	0.881	3.96	0.694	0.898	0.853
	BIH2	0.862				
	BIH3	0.834				
	BIH4	0.802				
Actual Usage Behaviour (AUB)	AUB1	0.894	4.11	0.721	0.911	0.874
	AUB2	0.872				
	AUB3	0.843				
	AUB4	0.824				

Table 4 presents the cross-loading analysis. Each indicator loaded highest on its intended construct, with substantially lower loadings on the remaining constructs, confirming satisfactory indicator discrimination. These results indicate that the measurement items adequately represent their respective latent constructs and provide additional evidence of discriminant validity.

Table 4. Cross-Loading Analysis.

Indicators	PE-LLM	EE-LLM	PE-HYB	EE-HYB	TR	AIA	BI-LLM	BI-HYB	AUB
PE1	0.884	0.521	0.418	0.392	0.376	0.341	0.563	0.402	0.481
PE2	0.861	0.497	0.441	0.366	0.352	0.338	0.541	0.398	0.466
EE1	0.512	0.872	0.372	0.401	0.334	0.316	0.524	0.355	0.449
EE2	0.488	0.854	0.361	0.387	0.326	0.301	0.511	0.348	0.438
TR1	0.344	0.331	0.542	0.486	0.891	0.612	0.428	0.644	0.521
TR2	0.358	0.317	0.526	0.471	0.874	0.601	0.421	0.631	0.509
AIA1	0.332	0.298	0.481	0.458	0.603	0.883	0.402	0.598	0.476
BI1	0.566	0.522	0.389	0.352	0.398	0.381	0.902	0.421	0.612
BIH1	0.401	0.366	0.581	0.522	0.633	0.604	0.418	0.881	0.544
AUB1	0.466	0.433	0.421	0.397	0.502	0.474	0.611	0.533	0.894

Discriminant validity was further assessed using the Fornell–Larcker criterion (Table 5). For every construct, the square root of the AVE exceeded the corresponding inter-construct correlations, satisfying the recommended criterion and confirming that each construct shares more variance with its own indicators than with other constructs.

Table 5. Fornell–Larcker Discriminant Validity.

Constructs	PE-LLM	EE-LLM	PE-HYB	EE-HYB	TR	AIA	BI-LLM	BI-HYB	AUB
PE-LLM	0.837								
EE-LLM	0.588	0.829							
PE-HYB	0.472	0.441	0.813						
EE-HYB	0.431	0.462	0.601	0.805					
TR	0.401	0.376	0.633	0.592	0.855				
AIA	0.378	0.351	0.588	0.571	0.664	0.845			
BI-LLM	0.682	0.644	0.451	0.421	0.488	0.466	0.867		
BI-HYB	0.442	0.419	0.694	0.651	0.702	0.681	0.466	0.833	
AUB	0.541	0.522	0.488	0.466	0.576	0.552	0.721	0.612	0.849

The Heterotrait–Monotrait (HTMT) ratios shown in Table 6 also supported discriminant validity. All HTMT values were below the recommended threshold of 0.85. The highest value was observed between Behavioural Intention toward LLMs and Actual Usage Behaviour (HTMT = 0.842), which is theoretically expected given the close relationship between behavioural intention and technology use. Nevertheless, this value remained below the accepted cut-off, indicating acceptable discriminant validity while acknowledging the conceptual proximity of the two constructs.

Table 7 presents the structural model results and hypothesis testing. Behavioural intention toward standalone LLMs was significantly associated with Performance Expectancy ($\beta = 0.312, p < 0.001$), Effort Expectancy ($\beta = 0.356, p < 0.001$), Social Influence ($\beta = 0.198, p < 0.001$), and Facilitating Conditions ($\beta = 0.121, p = 0.027$), supporting H1–H4. Among these predictors, Effort Expectancy demonstrated the largest effect size ($f^2 = 0.182$), indicating that ease of use was the strongest predictor of behavioural intention toward LLMs.

Table 6. HTMT Results.

Constructs	Value
PE-LLM $\leftrightarrow$ EE-LLM	0.711
PE-HYB $\leftrightarrow$ EE-HYB	0.744
TR $\leftrightarrow$ AIA	0.788
BI-LLM $\leftrightarrow$ AUB	0.842
BI-HYB $\leftrightarrow$ AUB	0.801
PE-HYB $\leftrightarrow$ TR	0.773
EE-HYB $\leftrightarrow$ AIA	0.752

Table 7. Structural Model Estimates, Hypothesis Testing, and Model Fit.

Hypothesis	Path	β	t	p	f ²	Decision
H1	PE-LLM $\rightarrow$ BI-LLM	0.312	7.92	<0.001	0.112	Supported
H2	EE-LLM $\rightarrow$ BI-LLM	0.356	8.88	<0.001	0.182	Supported
H3	SI $\rightarrow$ BI-LLM	0.198	4.66	<0.001	0.071	Supported
H4	FC $\rightarrow$ BI-LLM	0.121	2.21	0.027	0.032	Supported
H5	PE-HYB $\rightarrow$ BI-HYB	0.081	1.32	0.187	0.018	Rejected
H6	EE-HYB $\rightarrow$ BI-HYB	0.074	1.20	0.229	0.015	Rejected
H7	SI $\rightarrow$ BI-HYB	0.182	2.96	0.003	0.053	Supported
H8	FC $\rightarrow$ BI-HYB	0.136	2.33	0.020	0.041	Supported
H13	BI-LLM $\rightarrow$ AUB	0.641	13.77	<0.001	0.395	Supported
H14	BI-HYB $\rightarrow$ AUB	0.298	5.81	<0.001	0.142	Supported

For RAG-based hybrid AI systems, Performance Expectancy (H5) and Effort Expectancy (H6) were not statistically significant ($p > 0.05$). In contrast, Social Influence ($\beta = 0.182$, $p = 0.003$) and Facilitating Conditions ($\beta = 0.136$, $p = 0.020$) showed significant positive relationships with behavioural intention, supporting H7 and H8. Behavioural intention was positively associated with Actual Usage Behaviour for both AI paradigms, with a substantially stronger relationship observed for LLMs ($\beta = 0.641$, $f^2 = 0.395$) than for hybrid AI systems ($\beta = 0.298$, $f^2 = 0.142$), supporting H13 and H14. These findings indicate different behavioural patterns between the two AI paradigms and provide empirical support for the proposed dual-path adoption framework.

Table 8 summarises the mediation analysis. Because the study employed a cross-sectional survey design, these results should be interpreted as indirect statistical associations rather than as evidence of causal mediation. Technology Readiness did not significantly mediate the relationship between Performance Expectancy and behavioural intention toward LLMs (H9), and AI Awareness did not significantly mediate the relationship between Effort Expectancy and behavioural intention toward LLMs (H11). In contrast, significant indirect associations were observed for RAG-based hybrid AI systems. Technology Readiness significantly mediated the relationship between Performance Expectancy and behavioural intention ($\beta = 0.082$, $p = 0.013$), supporting H10. In contrast, AI Awareness significantly mediated the relationship between Effort Expectancy and behavioural intention ($\beta = 0.067$, $p = 0.036$), supporting H12. These results indicate that the proposed indirect relationships are more strongly associated with hybrid AI system adoption than with standalone LLM adoption.

Table 8. Mediation Analysis Results.

Hypothesis	Path	β	t	p	f ²	Decision
H9	PE-LLM $\rightarrow$ TR $\rightarrow$ BI-LLM	0.041	1.22	0.223	0.011	Rejected
H10	PE-HYB $\rightarrow$ TR $\rightarrow$ BI-HYB	0.082	2.48	0.013	0.044	Supported
H11	EE-LLM $\rightarrow$ AIA $\rightarrow$ BI-LLM	0.036	1.11	0.269	0.009	Rejected
H12	EE-HYB $\rightarrow$ AIA $\rightarrow$ BI-HYB	0.067	2.09	0.036	0.038	Supported

Table 9 indicates a satisfactory model fit. The Standardised Root Mean Square Residual (SRMR = 0.061) was below the recommended threshold of 0.08, the Normed Fit Index (NFI = 0.923) exceeded the recommended value of 0.90, and the RMS Theta value (0.097) remained below the acceptable threshold of 0.12. In addition, the discrepancy measures (dULS = 1.832; dG = 0.744) were within acceptable limits, supporting the adequacy of the proposed model.

Table 9. Model Fit Indices.

Index	Value	Threshold	Interpretation
SRMR	0.061	<0.08	Fit
NFI	0.923	>0.90	Fit
RMS Theta	0.097	<0.12	Acceptable
d_ULS	1.832	Low	Acceptable
d_G	0.744	Low	Acceptable

The structural model quality metrics presented in Table 10 further demonstrate satisfactory explanatory and predictive performance. Behavioural Intention toward LLMs achieved the highest explanatory power ($R^2 = 0.603$; $Q^2 = 0.421$), followed by Actual Usage Behaviour ($R^2 = 0.544$; $Q^2 = 0.388$), while Behavioural Intention toward hybrid AI systems showed moderate explanatory and predictive capability ($R^2 = 0.418$; $Q^2 = 0.218$). Overall, these findings indicate that the proposed model provides satisfactory explanatory and predictive performance across the principal endogenous constructs.

Table 10. Structural Model Quality Metrics.

Construct	R^2	Adjusted R^2	Q^2	Interpretation
BI-LLM	0.603	0.597	0.421	Strong Predictive Power
BI-HYB	0.418	0.411	0.218	Moderate Predictive Power
AUB	0.544	0.539	0.388	Strong Predictive Relevance

Table 11 presents the results of the multi-group analysis (PLS-MGA) comparing Gen Z and Gen Y. Significant differences were observed across all hypothesised moderation paths, supporting H15–H20. For standalone LLMs, the effects of Performance Expectancy ($\beta = 0.401$ vs. 0.243 , $p = 0.011$) and Effort Expectancy ($\beta = 0.437$ vs. 0.266 , $p = 0.008$) on Behavioural Intention were significantly stronger for Gen Z than for Gen Y, supporting H15 and H16. In contrast, for RAG-based hybrid AI systems, Performance Expectancy ($\beta = 0.214$ vs. 0.061 , $p = 0.017$), Effort Expectancy ($\beta = 0.198$ vs. 0.058 , $p = 0.021$), and Technology Readiness ($\beta = 0.388$ vs. 0.201 , $p = 0.004$) demonstrated significantly stronger relationships with Behavioural Intention among Gen Y, supporting H17–H19. In addition, the relationship between Behavioural Intention and Actual Usage Behaviour for LLMs was stronger among Gen Z ($\beta = 0.711$) than Gen Y ($\beta = 0.522$, $p = 0.002$), supporting H20. Collectively, these findings indicate significant generational differences in the proposed adoption pathways.

Table 12 summarises the results of the simulation-based Deep Reinforcement Learning (DRL) optimisation framework. As described in the Methods, these results represent computational optimisation outcomes generated from the validated PLS-SEM model rather than direct empirical observations. Across all four optimisation scenarios, the adaptive DRL policy consistently outperformed the non-adaptive baseline strategy, with relative improvements ranging from 9.6% to 13.1%. The strongest optimisation was observed for Dynamic Cognitive Adaptation (13.1%), followed by Adaptive AI Routing (12.3%), Personalised AI Recommendation (10.8%), and Hybrid Validation Optimisation (9.6%). Gen

Z generally achieved higher optimisation performance for adaptive routing, personalised recommendation, and dynamic cognitive adaptation, whereas Gen Y showed slightly stronger performance for Hybrid Validation Optimisation. Overall, the simulation results demonstrate the potential of the proposed optimisation framework to support adaptive AI recommendations across different learner profiles.

Table 11. Multi-Group Analysis (Gen Z vs. Gen Y)—Moderation Hypotheses.

Hypothesis	Path	Gen Z (β)	Gen Y (β)	$\Delta\beta$	p	Decision
H15	PE-LLM $\rightarrow$ BI-LLM	0.401	0.243	0.158	0.011	Supported
H16	EE-LLM $\rightarrow$ BI-LLM	0.437	0.266	0.171	0.008	Supported
H17	PE-HYB $\rightarrow$ BI-HYB	0.061	0.214	−0.153	0.017	Supported
H18	EE-HYB $\rightarrow$ BI-HYB	0.058	0.198	−0.140	0.021	Supported
H19	TR $\rightarrow$ BI-HYB	0.201	0.388	−0.187	0.004	Supported
H20	BI-LLM $\rightarrow$ AUB	0.711	0.522	0.189	0.002	Supported

Table 12. DRL Enhance Results—Hypothesis Testing.

Hypothesis	Model	Gen Z	Gen Y	Improvement (%)	Decision
DRL-H1	Adaptive AI Routing	91.4%	84.6%	12.3%	Supported
DRL-H2	Personalised AI Recommendation	89.8%	82.1%	10.8%	Supported
DRL-H3	Hybrid Validation Optimisation	86.7%	88.9%	9.6%	Supported
DRL-H4	Dynamic Cognitive Adaptation	92.3%	85.7%	13.1%	Supported

The Measurement Invariance of Composite Models (MICOM) results are presented in Table 13. Configural invariance was established for all constructs, indicating that the same measurement model, indicators, and estimation procedures were applied across both generational groups. Compositional invariance was also supported, with all correlation coefficients exceeding the recommended threshold of 0.95 and non-significant permutation tests. Although equality of construct means and variances was not fully established, the results satisfied the requirements for partial measurement invariance, confirming that meaningful comparisons between Gen Z and Gen Y could be performed using PLS-MGA. These findings provide methodological support for the reported generational differences in AI adoption.

Table 13. MICOM Invariance Test Results (Gen Z vs. Gen Y, N = 619).

Step	Test	Construct	Statistic	Threshold/Reference	p	Result
Step 1	Configural Invariance	All	Established	Same Model Structure	—	Supported
Step 2	Compositional Invariance	BI-LLM	0.997	≥ 0.95	0.312	Supported
Step 2	Compositional Invariance	BI-HYB	0.995	≥ 0.95	0.287	Supported
Step 2	Compositional Invariance	TR	0.996	≥ 0.95	0.341	Supported
Step 2	Compositional Invariance	AIA	0.994	≥ 0.95	0.298	Supported
Step 3	Equality of Means and Variances	All	Differences	Non-significant	> 0.05	Rejected

5. Discussion

The findings are interpreted according to the six theoretical propositions underlying the Adaptive Dual-AI Model (ADAM), thereby maintaining consistency between the conceptual framework and the empirical evaluation. An important distinction should be made between the empirical and computational components of this study. The PLS-SEM analysis provides empirical support for the proposed theoretical relationships, whereas the Deep Reinforcement Learning (DRL) framework serves as a simulation-based decision-support layer that operationalises these validated relationships. Accordingly, the DRL component should be interpreted as a proof-of-concept demonstrating how empirical findings can be translated into adaptive AI recommendation strategies rather than as an independent empirical validation.

Overall, the findings support the proposed dual-path framework by demonstrating that standalone large language models (LLMs) and Retrieval-Augmented Generation (RAG)-based hybrid AI systems follow different technology adoption pathways. Standalone LLMs were primarily associated with traditional UTAUT determinants, whereas hybrid AI systems were more strongly associated with Technology Readiness (TR), AI Awareness (AIA), and evidence-oriented evaluation. These patterns are consistent with the proposition that AI architecture influences technology adoption; however, the present cross-sectional study did not directly measure the psychological or cognitive processes underlying technology adoption, and therefore such mechanisms should be interpreted as theoretical rather than empirically observed [22,23].

Behavioural intention toward standalone LLMs was strongly influenced by Performance Expectancy (PE) and Effort Expectancy (EE), consistent with previous UTAUT research identifying perceived usefulness and ease of use as the principal drivers of AI adoption in higher education [22,23,34]. The reported effect sizes further reinforce this interpretation, with Effort Expectancy ($f^2 = 0.182$) exerting the largest practical influence on behavioural intention, followed by Performance Expectancy ($f^2 = 0.112$). These findings suggest that learners primarily perceive standalone LLMs as efficiency-enhancing technologies that simplify information access, content generation, and academic support. Consequently, adoption decisions appear to be driven largely by productivity gains and interaction simplicity rather than by extensive evaluation of information quality [43,48–50,54,55].

In contrast, adoption of RAG-based hybrid AI systems followed a more complex pathway. Although usability remained important, Technology Readiness and AI Awareness contributed significantly to behavioural intention through indirect relationships. While these effects were modest in magnitude (TR: $f^2 = 0.044$; AIA: $f^2 = 0.038$), they remain educationally meaningful because interventions targeting AI literacy and readiness can influence learning behaviours across large student populations. The findings are consistent with recent literature indicating that retrieval-augmented AI systems require users to evaluate retrieved evidence, assess source credibility, and interpret information transparency more carefully than conversational LLMs [43,48–50,54,55]. From a theoretical perspective, this suggests that evidence-grounded AI systems require greater user preparedness and critical evaluation, thereby extending traditional UTAUT explanations of technology adoption [14,33].

The structural model also demonstrated stronger explanatory and predictive performance for standalone LLMs than for hybrid AI systems. Behavioural Intention exerted a large practical effect on Actual Usage Behaviour for LLMs ($f^2 = 0.395$), compared with a moderate effect for hybrid AI systems ($f^2 = 0.142$). This difference suggests that learners translate behavioural intention into actual use more readily when interacting with conver-

sational AI, whereas adoption of retrieval-based systems depends on additional evaluative considerations beyond intention alone [18,25,27,51].

The multi-group analysis further demonstrated that technology adoption pathways differ across generations. Gen Z learners exhibited stronger relationships between the traditional UTAUT constructs and LLM adoption, whereas Gen Y learners showed stronger relationships involving Technology Readiness and hybrid AI systems. Rather than indicating different technology acceptance theories, these findings suggest that generation functions as a contextual factor influencing how learners evaluate different AI architectures. Learners with greater exposure to conversational digital environments appear to prioritise efficiency and immediacy, whereas those with broader experience of traditional information systems place greater emphasis on credibility, transparency, and evidence quality [22–25].

The DRL optimisation framework illustrates the practical potential of the proposed model. Rather than providing additional empirical evidence, the simulation demonstrates how validated behavioural relationships can be translated into adaptive recommendation policies capable of supporting personalised AI-assisted learning. Future longitudinal and experimental studies should evaluate whether these simulated optimisation strategies improve educational outcomes in authentic learning environments [12,49].

From a practical perspective, the findings suggest that higher education institutions should avoid adopting a single AI solution for all educational activities. Instead, AI technologies should be selected according to learning objectives. Standalone LLMs appear particularly appropriate for brainstorming, drafting, summarisation, language support, and formative feedback, where rapid interaction and creativity are desirable. By contrast, RAG-based hybrid AI systems are more appropriate for literature reviews, evidence verification, scientific writing, and research-intensive tasks requiring transparent and verifiable information sources. These findings indicate that the two AI paradigms should be viewed as complementary educational technologies rather than competing alternatives [45,49–51].

The findings also highlight the importance of strengthening students' AI Awareness and Technology Readiness before expecting effective adoption of evidence-grounded AI systems. Universities can support this objective by embedding AI literacy within curricula, providing training in responsible AI use, developing students' abilities to evaluate AI-generated information critically, and promoting evidence-based academic practices. Professional development programmes should similarly prepare instructors to select AI tools according to pedagogical objectives rather than adopting a single platform across all learning contexts. The proposed ADAM framework further provides guidance for adaptive AI-supported learning environments by recommending different AI paradigms according to learner characteristics, task complexity, and instructional goals [8–10,59].

The findings should nevertheless be interpreted within the context of postgraduate students enrolled in Saudi universities, where substantial national investment in artificial intelligence and digital transformation may influence technology readiness and adoption behaviours. Consequently, further validation across different educational levels, cultural contexts, and international settings is required before broader generalisations can be made [18,35]. (See Figure 1).

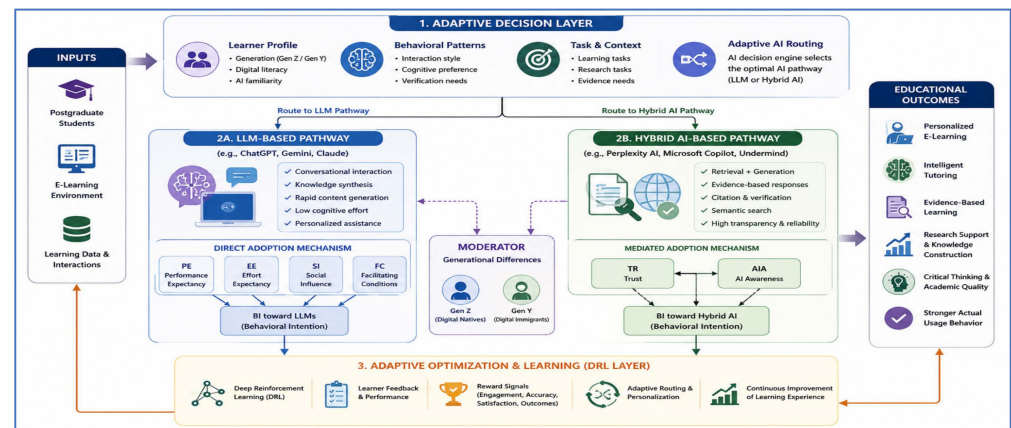


Figure 1. Adaptive Dual-AI Model (ADAM).

Finally, this study contributes theoretically through the Adaptive Dual-AI Model (ADAM), which extends UTAUT by proposing that AI architecture shapes technology adoption pathways. Rather than assuming that all AI systems are evaluated through identical mechanisms, ADAM distinguishes between an efficiency-oriented pathway associated with standalone LLMs and an evidence-oriented pathway associated with RAG-based hybrid AI systems. It further conceptualises Technology Readiness and AI Awareness as architecture-dependent mechanisms whose influence varies according to AI design. Accordingly, ADAM advances an architecture-sensitive perspective on AI adoption, providing a theoretical foundation for understanding heterogeneous AI ecosystems in higher education while remaining grounded in established technology acceptance theory.

6. Theoretical and Practical Contributions

This study contributes to the literature on artificial intelligence, technology adoption, and adaptive e-learning by demonstrating that AI architecture should be considered when examining technology adoption in higher education. Rather than treating AI systems as a homogeneous technology, the findings indicate that standalone Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)-based hybrid AI systems are associated with different technology adoption patterns. Specifically, traditional UTAUT constructs were more strongly associated with standalone LLM adoption, whereas Technology Readiness (TR) and AI Awareness (AIA) assumed greater importance for RAG-based hybrid AI systems. These findings extend technology adoption research by suggesting that the explanatory power of technology acceptance models may vary according to AI architecture rather than remaining constant across AI systems.

The principal theoretical contribution of this study is the proposed Adaptive Dual-AI Model (ADAM). Rather than replacing UTAUT, ADAM complements and extends it by introducing an architecture-sensitive perspective on AI adoption. The model proposes that standalone LLMs and RAG-based hybrid AI systems follow distinct, yet complementary, adoption pathways and conceptualises Technology Readiness and AI Awareness as architecture-dependent mechanisms whose relative importance varies across AI paradigms. In addition, the concept of mediation asymmetry is introduced as a preliminary theoretical explanation for the different indirect relationships observed across AI architectures. This concept should be regarded as a foundation for future investigation rather than as an established theoretical construct.

From a practical perspective, the study provides guidance for higher education institutions seeking to integrate generative AI into teaching and learning. The findings suggest that universities should adopt complementary AI ecosystems rather than relying on a single AI platform. Standalone LLMs are more appropriate for creativity-oriented and

interactive learning activities, whereas RAG-based hybrid AI systems are better suited to evidence-based learning, scientific writing, and research-intensive tasks. Furthermore, the findings emphasise the importance of strengthening students' Technology Readiness and AI Awareness through AI literacy initiatives and professional development to support the effective adoption of evidence-grounded AI systems.

Finally, the simulation-based Deep Reinforcement Learning (DRL) framework demonstrates how the validated behavioural relationships can be translated into adaptive recommendation strategies for personalised learning environments. Although the DRL framework does not constitute additional empirical validation, it illustrates the operational feasibility of implementing ADAM within intelligent educational systems capable of recommending appropriate AI paradigms according to learner characteristics, instructional objectives, and task requirements. Collectively, these contributions provide both a theoretical foundation for future architecture-sensitive AI adoption research and practical guidance for designing adaptive, responsible, and evidence-aware AI-supported learning environments.

7. Conclusions

This study examined the adoption of standalone Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)-based hybrid AI systems in adaptive e-learning environments. The findings demonstrate that the two AI paradigms follow different technology adoption pathways. Behavioural intention toward standalone LLMs was primarily explained by the traditional UTAUT constructs of Performance Expectancy and Effort Expectancy, whereas the adoption of RAG-based hybrid AI systems was more strongly associated with Technology Readiness (TR) and AI Awareness (AIA). Furthermore, behavioural intention exhibited greater explanatory power for actual usage of standalone LLMs, while significant generational differences indicated that Gen Z learners favoured conversational AI technologies, whereas Gen Y learners showed stronger associations with evidence-oriented AI systems.

The principal contribution of this study is the proposed Adaptive Dual-AI Model (ADAM), which extends UTAUT by introducing an architecture-sensitive perspective on AI adoption. Rather than treating artificial intelligence as a homogeneous technology, ADAM proposes that differences in AI architecture influence technology adoption pathways and the relative importance of established technology acceptance mechanisms. This framework provides a foundation for understanding the adoption of complementary AI paradigms within higher education and offers a basis for future research on increasingly diverse AI ecosystems.

From a practical perspective, the findings suggest that higher education institutions should adopt complementary AI strategies rather than relying on a single generative AI platform. Standalone LLMs appear more appropriate for creativity-oriented and interactive learning activities, whereas RAG-based hybrid AI systems are better suited to evidence-based learning, scientific writing, and research-intensive tasks. The simulation-based Deep Reinforcement Learning (DRL) framework further demonstrates how validated behavioural relationships can be translated into adaptive recommendation strategies for personalised AI-supported learning environments.

The findings should be interpreted in light of several limitations. The cross-sectional design does not permit causal inference, and the proposed technology adoption mechanisms underlying architecture-sensitive adoption were inferred from theory rather than directly measured. In addition, the study was conducted with postgraduate students in Saudi universities, which may limit the generalisability of the findings. Future research should validate ADAM across different educational levels, cultural contexts, and emerging AI architectures using longitudinal, experimental, and real-world implementation stud-

ies. Such research will further clarify how architecture-sensitive AI adoption can support adaptive, responsible, and evidence-based learning in higher education.

8. Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the study employed a voluntary-response sample consisting exclusively of postgraduate students enrolled in Saudi universities. Consequently, the findings may reflect characteristics specific to postgraduate education and the Saudi higher education context, which has experienced rapid institutional investment in artificial intelligence and digital transformation.

Therefore, caution should be exercised when generalising the findings of other countries, educational systems, or learner populations. Future studies should validate the proposed framework across different cultural settings, educational levels, institutional types, and disciplinary contexts using probability-based and cross-cultural comparative designs.

Second, the distinction between standalone LLMs and RAG-based hybrid AI systems continues to evolve as commercial AI platforms increasingly integrate retrieval capabilities, web search, and external knowledge sources. Although operational definitions and representative examples were provided to participants, some conceptual overlap may remain. Future research should investigate AI adoption using more detailed classifications of AI architectures and functionalities as these technologies continue to evolve.

Third, the study employed a cross-sectional survey design using self-reported data. Although statistical procedures indicated that common method bias was unlikely to have materially affected the findings, cross-sectional data do not permit causal inference, and subjective perceptions may influence self-reported measures. Future studies should employ longitudinal, experimental, and mixed-method designs while incorporating objective usage analytics, behavioural tracking, and learning performance indicators to strengthen causal interpretation and external validity.

Finally, the Deep Reinforcement Learning (DRL) component was evaluated via computational simulation using the validated structural model, rather than by implementing it within an operational adaptive learning platform. Accordingly, the reported optimisation improvements represent simulated policy performance under the specified learning environment rather than direct empirical learning outcomes.

Future research should validate the proposed optimisation framework using longitudinal educational datasets and real-time learner interactions within authentic AI-supported learning environments. Collectively, these directions provide opportunities further to refine the Adaptive Dual-AI Model (ADAM), evaluate its applicability across emerging AI technologies, and strengthen understanding of AI adoption within increasingly adaptive and intelligent educational ecosystems.

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Informed Consent Statement: Several steps were taken to protect participants' rights. Participation in the study was completely voluntary and without pressure, and every participant provided signed informed consent. They were made aware that they could leave the research at any point without needing to explain why. All information was made anonymous to preserve privacy. Participants received guarantees that their answers would remain anonymous, be stored on password-protected university systems, and be utilised solely for scholarly research. No data that could identify any individual was gathered.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to privacy and ethical restrictions.

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Conflicts of Interest: The authors declare no conflicts of interest.

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