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The Role of AI Tools in Enhancing Student Satisfaction and Learning Outcomes in Developing Countries

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Abstract

Purpose - This study examines the determinants of students' acceptance and use of artificial intelligence (AI)-based academic support systems in higher education. It focuses on how performance expectancy, information accuracy, and pedagogical fit influence behavioral intention, actual use, and academic performance of the students. Additionally, this study evaluated the mediating roles of behavioral intention and satisfaction in shaping students' learning experiences in AI-enabled environments across different institutional contexts.

Design/methodology/approach - An extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework is employed using cross-sectional survey data collected from students in higher education institutions in the United Arab Emirates (UAE) and India. Structural Equation Modeling (SEM) was applied to examine the relationships among the constructs. A mediation analysis was conducted to capture indirect effects, and cross-country validation was performed to assess the robustness and generalizability of the model across diverse educational settings.

Findings - The findings revealed that performance expectancy, information accuracy, and pedagogical fit significantly enhanced students' behavioral intention to adopt AI-based tools ($p < 0.01$). Behavioral intention positively influences actual usage, which, in turn, improves student satisfaction and academic performance. Satisfaction and behavioral intention were significant mediating mechanisms in the model. Cross-country analysis confirms the structural consistency of the framework, with minor variations reflecting the contextual differences between the UAE and India.

Originality/Value - This study extends the UTAUT framework by integrating AI-specific constructs, including information accuracy and pedagogical fit, into a unified behavioral model. By providing cross-country empirical evidence and incorporating both cognitive and affective mechanisms, this study offers a comprehensive understanding of AI adoption in higher education. Importantly, this study contributes to decision science by explaining how students' behavioral intentions and satisfaction shape technology adoption decisions and learning outcomes in AI-enabled environments. It provides evidence-based insights for policymakers and educators to support informed decision-making regarding AI integration, resource allocation, and strategic planning in conditions of technological uncertainty.

Keywords: Artificial Intelligence, Higher Education, Student Satisfaction, Learning Outcomes, Technology Adoption, UAE, India

JEL Classifications: I23, O33, C52, I21

1 Introduction

Artificial intelligence (AI) has been identified as a disruptive technology that is drastically changing the educational landscape of higher education institutions by transforming approaches related to teaching, learning, and assessment processes (Ahmad et al., 2021; AlDhaen, 2022). With a large number of AI technologies, from chatbot-based intelligent learning platforms to AI-driven learning analytics platforms, being developed at a faster pace, it has now resulted in improving learning personalization and administrative efficiency, as well as enhancing learning effectiveness at higher education institutions. Chatterjee and Bhattacharjee (2020) corroborated that in light of the sudden outbreak of the COVID-19 global pandemic, it has been seen that institutions of higher education are rapidly embracing AI-driven learning platforms for ensuring academic continuity. In developing economies like India and the UAE, institutions of higher education now consider using AI tools as a major priority in education, while AI innovation policies—such as India's Digital Educational Mission and the UAE's Vision 2031—emphasize the strategic integration of artificial intelligence in education.

Despite the increased integration of AI technology into education, there remains a relative lack of empirical evidence on acceptance, intentions to use, and user satisfaction with AI-supported academic assistance systems by students. Prior studies have identified performance expectancy, effort expectancy, facilitating conditions, and social influence as key constructs that influence technology acceptance and utilization in educational settings (Almaiah et al., 2019; Venkatesh et al., 2003). However, the shift from the previous LMS to AI-powered learning systems brings new constructs that merit detailed study (Alenezi, 2022; Al-Rahmi et al., 2023). AI-powered learning systems enable instant feedback, automated assessments, and user engagement that mimic human-like interactions with learning materials (Ahmad & Ghapar, 2019b). On the other hand, student acceptance of AI-powered learning systems largely hangs on their accuracy levels for academic relevance to learning objectives (Caratiquit & Caratiquit, 2023)

The current literature provides valuable but fragmented insights into the factors influencing AI adoption in education. Indeed, the majority of previous efforts that explored AI adoption did so with a country- or application-level focus, neglecting the influence of context, behavior, or other factors of a conversational or personal nature, including student engagement or personal innovation characteristics, as in Alkawsi et al. (2021). Furthermore, there appears to be a lack of literature that comprehensively investigates how AI can be successfully adopted to achieve specific academic performance indicators of AI adoption, including performance or satisfaction levels, in a different context of a respective culture.

To fill this research gap, the current study investigates the factors that affect the acceptance and use of AI-assisted learning aids by higher educational institutions in UAE and India. Based on the expansion of the Unified Theory of Acceptance and Use of Technology framework presented by Venkatesh et al. (2003), a broader descriptive framework encompassing information accuracy, pedagogical fit, and technology interaction perspectives, along with other moderating variables of student engagement and personal innovativeness to highlight individual differences with respect to behavior and performance tailored by Dahri et al. (2024), has been followed by the current study for its theoretical underpinnings.

This study had four objectives. First, to identify the key determinants influencing students' behavioral intentions and actual use of AI tools in higher education. Second, it evaluates how technological factors such as performance expectancy, information accuracy, and pedagogical fit contribute to adoption decisions. Third, the mediating role of satisfaction in linking AI tool usage to academic performance was analyzed.

This study has significance in the literature in several ways. First, it expands the UTAUT model by adding AI-specific constructs, such as the accuracy of information, pedagogical fit, and technology interaction, making it more applicable to intelligent learning settings. Second, it presents satisfaction as a mediating factor between AI tool use and academic achievement, providing a more in-depth perspective of the cognitive-affective-behavioral process. Third, the research provides cross-country results for the UAE and India, which adds to the overall modeling of the relevance of AI adoption models in different educational settings.

2 Literature Review and Theoretical Framework

2.1 Literature Review

The integration of artificial intelligence (AI) into higher education has significantly transformed the teaching, learning, and assessment processes. In the context of personalized learning, real-time feedback, and enhanced performance, AI-driven tools, such as intelligent tutoring, automated grading, and adaptive learning systems, have been used (Ahmad et al., 2021; Ali et al., 2022; Chatterjee & Bhattacharjee, 2020). The development of AI technologies in higher education has gained momentum in countries such as the United Arab Emirates (UAE) and India, following the switch to a digital learning environment, which specifically presupposes the impact of the COVID-19 pandemic.

The foundational contributions to AI in education can be traced to early pioneers such as Baker and Yacef (2009), who established educational data mining frameworks, and Luckin and Holmes (2016), who articulated the intelligence-augmentation perspective in learning environments. Woolf et al. (2013) provided an early comprehensive roadmap for AI tutoring systems, while Roll and Wylie (2016) synthesized the evolution of intelligent tutoring from rule-based systems to adaptive learning platforms. More recent scholarship has extended these foundations by examining generative AI's role in personalized learning (Chiu, 2024; Crompton & Burke, 2023; Hwang & Chen, 2023; Kuleto et al., 2021; Sun et al., 2025; Zawacki-Richter et al., 2019; Zhang & Aslan, 2021).

The application of technology in the learning environment has also been the subject of numerous theoretical expositions through a set theoretical framework, with one of the most significant being the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The UTAUT model assumes that the main predictors of the intention to use technology are performance expectancy, effort expectancy, social influence, and enabling conditions. All these factors are determinants of the willingness to adopt technology and consequent usage behavior among users. Its model has been widely tested in other types of situations, such as e-learning platforms and digital education systems (Almaiah et al., 2019; Bagadeem et al., 2024; Venkatesh et al., 2012).

Despite its strengths, the implementation of UTAUT in AI-based education systems requires some improvements. The distinguishing features of AI technologies compared to traditional systems are their capability to offer intelligent suggestions, automated decisions, and adaptive learning paths. These attributes bring new dimensions that are not well represented in the original UTAUT constructs. Recent research highlights information accuracy, pedagogical fit, and interactions with technology as crucial factors in controlling user behavior within AI-driven environments (Alenezi, 2022; Al-Rahmi et al., 2023; Chang et al., 2023).

The accuracy of information is a concern that shows the reliability and correctness of AI-generated information, and it is essential in education, where students depend on such information to learn and be assessed. An increased level of accuracy boosts user confidence and stimulates its use, while errors can decrease and restrict its usage (Filieri & McLeay, 2014; Foroughi et al., 2023). The attitude of AI tools towards instructional goals is called pedagogical fit, which guarantees that technology helps achieve positive learning outcomes (Chang et al., 2024; Pittalis, 2021; Roy et al., 2020). The capability of AI systems to promote communication, feedback, and interaction is known as technology interaction and reveals the possibility of dynamic and interactive learning environments (Ouyang et al., 2022). From an institutional perspective, Herman and Khalaf (2023) demonstrated that academic supervision and decision-making processes significantly influence teacher performance and technology integration, underscoring the importance of leadership and administrative support in educational technology adoption.

In addition to technological factors, personal characteristics are also influential in the adoption of technology. The cognitive and emotional participation of students can be observed in student engagement, thus making AI tools more effective and improving learning outcomes (Al-Fraihat et al., 2017; Chen et al., 2024; Tu et al., 2023). Personal innovativeness is an individual's behavior that implies readiness to use new technologies, and it helps to evaluate the process of transitioning intention into practice (Amin & Rajadurai, 2018).

Although previous research is informative, some gaps still exist. First, most studies can be confined to the analysis of one country, which ultimately minimizes the validity of conclusions regarding the situation in a variety of schools. Second, the mediation of satisfaction between AI usage and academic performance has not been researched. Third, integrative frameworks that co-incorporate technology, pedagogical, and behavioral aspects are lacking.

The current study fills these gaps by expanding the UTAUT model and adding new constructs, such as accuracy of information, pedagogical fit, and technology interaction, as well as moderating variables, such as student engagement and personal innovativeness. In addition, a mediating variable is proposed, namely satisfaction, as the variable between the use of AI and academic performance, to provide a more comprehensive view of learning outcomes.

2.2 *Theoretical Framework and Model Specification*

Extensions of the UTAUT framework for educational contexts have been progressively developed by pioneering scholars, including Taylor and Todd (1995a, 1995b), who introduced decomposed TPB, and Thompson et al. (1991), who incorporated PC utilization constructs. More recent theoretical advances have integrated AI-specific dimensions, including perceived intelligence and anthropomorphism (Gursoy et al., 2019; Kelly et al., 2023; Masrek et al., 2025; Mukhamedkarimova & Umurkulova, 2025).

The Unified Theory of Acceptance and Use of Technology (UTAUT) is the foundational theory of the present study, as it attempts to integrate several theoretical viewpoints, such as the Technology Acceptance Model, Theory of Planned Behavior, and Innovation Diffusion Theory, to explain technology adoption behavior (Venkatesh et al., 2003). It also assumes that behavioral intention depends on performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), which, in turn, determine actual usage behavior.

The UTAUT approach is specified as follows:

$$BI = f(PE, EE, SI, FC), \tag{1}$$

$$AU = f(BI, FC), \tag{2}$$

where BI (Behavioral Intention) indicates the technology adoption intention and AU (Actual Use) demonstrates the realized usage behavior. These equations suggest that behavioral intention is largely influenced by the perception of usefulness, ease of use, social pressures, and support offered by the users, and actual use is influenced by intention and the enabling conditions that allow the adoption of technology.

Nonetheless, in technology-mediated learning contexts, contact with technology is much more disengaged and personalized. Therefore, the impact of social influence is comparatively minor and is not considered in the current study. This exclusion aligns with recent trends in the literature that dwell on the importance of self-directed use of technology in digital learning situations.

The UTAUT model was further expanded to include other constructs of technological quality, pedagogical alignment, and interaction with the user to better represent the complexity of AI-based systems. The extended model is specified as follows:

$$BI = f(PE, EE, FC, IA, PF, TI, SE, PI), \tag{3}$$

$$AU = f(BI, PI), \tag{4}$$

$$SS = f(AU, IA, PF, SE), \tag{5}$$

$$AP = f(SS), \tag{6}$$

where IA, PF, TI, SE, PI, SS, and AP indicate information accuracy, pedagogical fit, technology interaction, student engagement, personal innovativeness, satisfaction, and academic performance, respectively. Such interrelated equations provide evidence that behavioral intention is indirectly affected by traditional factors of UTAUT and AI-specific characteristics and individual factors, whereas actual use, satisfaction, and academic performance are connected by a series of relationships, both direct and moderate in nature, within the learning process.

To operationalize these associations, the approach is expressed in linear form as follows:

Behavioral Intention:

$$BI_i = \alpha_0 + \alpha_1 PE_i + \alpha_2 EE_i + \alpha_3 FC_i + \alpha_4 IA_i + \alpha_5 PF_i + \alpha_6 TI_i + \alpha_7 SE_i + \alpha_8 PI_i + \varepsilon_i, \tag{7}$$

where $\alpha_0$represents the intercept term, $\alpha_1 - \alpha_8$denote the slope coefficients capturing the marginal effects of Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Information Accuracy (IA), Pedagogical Fit (PF), Technology Interaction (TI), Student Engagement (SE), and Personal Innovativeness (PI) on Behavioral Intention (BI), and ε_i represents the stochastic error term capturing unobserved influences. According to this Equation, behavioral intention is predicted by an interaction between technological, pedagogical, and personal factors, where each of these coefficients indicates the marginal contribution of a particular construct.

Actual Use:

$$AU_i = \beta_0 + \beta_1 BI_i + \beta_2 (BI_i \times PI_i) + \mu_i, \tag{8}$$

where β_0 represents the intercept term, β_1 and β_2 denote the slope coefficients capturing the direct effect of Behavioral Intention (BI) and its interaction with Personal Innovativeness (PI) on Actual Use (AU), and μ_i represents the stochastic error term accounting for unobserved variations. The formulation emphasizes that behavioral intention directly impacts actual use and personal innovativeness enhances this relationship; it has an interaction effect.

Satisfaction:

$$SS_i = \gamma_0 + \gamma_1 AU_i + \gamma_2 IA_i + \gamma_3 PF_i + \gamma_4 (AU_i \times SE_i) + \nu_i, \tag{9}$$

where γ_0 represents the intercept term, $\gamma_1 - \gamma_4$denote the slope coefficients capturing the effects of Actual Use (AU), Information Accuracy (IA), Pedagogical Fit (PF), and the interaction between Actual Use and Student Engagement (SE) on Satisfaction (SS), and ν_i represents the stochastic error term reflecting unobserved influences. This Equation illustrates the relationship between actual use and other system-related factors and the moderation of the influence of usage and satisfaction on student engagement.

Academic Performance:

$$AP_i = \delta_0 + \delta_1 SS_i + \omega_i, \tag{10}$$

where δ_0 represents the intercept term, δ_1 denotes the slope coefficient capturing the effect of Satisfaction (SS) on Academic Performance (AP), and ω_i represents the stochastic error term capturing unobserved variations in academic performance. These equations were estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM), which allows the simultaneous estimation of multiple interdependent relationships involving mediation and moderation effects. PLS-SEM is especially suitable for this study because the proposed model is quite complex, involving technological, pedagogical, and behavioral aspects. In addition, PLS-SEM is a variance method that is highly applicable in social science and educational research settings because it does not make rigid assumptions about the normality of data (Hair, 2021). Moreover, with its moderately sized sample size and the existence of various latent variables that have complicated structural paths, PLS-SEM delivers strong and trustworthy estimates of parameters.

Comprehensively, this multi-layered approach brings together an array of technological, pedagogical, and behavioral factors to offer a multi-faceted explanation of AI implementation in higher education, which is specifically relevant to cross-country settings, including the UAE and India.

2.3 Extension of the UTAUT Model for the Educational AI Context

Although UTAUT remains a robust platform for analyzing technology acceptance, it does not comprehensively represent the continuously evolving and knowledge-oriented environment that AI technology embodies. It was therefore concluded that the study would add to this theory by considering other constructs like Information Accuracy (IA), Pedagogical Fit (PF), Technology Interaction (TI), Student Engagement (SE), and Personal Innovativeness (PI), as suggested by Dahri et al. (2024) and Al-Rahmi et al. (2023).

2.3.1 Performance Expectancy (PE)

Performance Expectancy refers to the extent to which users believe that the AI system can enhance their learning efficiency or performance. Different studies have established that Performance Expectancy continues to influence behavioral intention concerning technology adoption. In the AI learning environment, Performance Expectancy encompasses efficiency, creativity, and understanding derived from intelligent systems (Ahmad & Ghapar, 2019a; Fan et al., 2025).

2.3.2 Effort Expectancy (EE)

Effort Expectancy measures the extent to which users believe that AI-based systems are easy to use. Almaiah et al. (2019) found that ease of use makes students more likely to utilize AI-supported tools if they find them user-friendly. This factor also influences users to smoothly integrate AI-based tools with minimal cognitive or technical difficulties, as argued by Al-Rahmi et al. (2022).

2.3.3 Facilitating Conditions (FC)

Facilitating Conditions represent factors that influence the availability of institutional resources that aid students in successfully utilizing AI. Such factors include infrastructure, Internet availability, and staff assistance. Researchers have stressed that quality facilitating conditions help create positive behavioral intentions toward constant technology application (AlDhaen, 2022; Gohar et al., 2023). Support or readjustment for AI-based learning initiatives in developing learning ecosystems, such as the UAE and India, or other countries, requires significant attention to facilitating conditions.

2.3.4 Information Accuracy (IA)

Information Accuracy: Information accuracy refers to the accuracy, credibility, and relevance of AI-generated output. Being AI-driven, learning content as well as related recommendations generated automatically influence students' trust in such technologies as accuracy perceptions lie at the heart of trust, as noted by Alenezi (2022) and Filieri and McLeay (2014). Accuracy in information promotes users' trust and satisfaction, whereas inaccuracies influence distrust, as noted by Foroughi et al. (2023).

2.3.5 Pedagogical Fit (PF)

Pedagogical Fit, which refers to a technology's compatibility with learning objectives, curriculum content, or learning strategies, became a focal point of study during this period, with research being conducted by Pittalis (2021), as well as by Roy et al. (2020). Technologies that work in accordance with learning requirements or teaching practices stand a greater chance of being embraced by both students and teachers.

2.3.6 Technology Interaction (TI)

Technology Interaction refers to the interactive and communicative capabilities of AI that help engage users and contribute to active learning (Caratiquit & Caratiquit, 2023; Gohar et al., 2022). Technologically interactive components, such as chatbot conversational components, adaptive feedback, and instant evaluations, contribute to a dynamically active learning environment that continuously requires active participation by users (Ouyang et al., 2022). The empirical results validate that system interactivity positively impacts both satisfaction and learning effectiveness.

2.3.7 Student Engagement (SE)

Student Engagement serves as a moderating variable that measures the emotional and psychological participation of students in AI-supported learning processes. Engaged students display strong motivation, perseverance, and flexibility in technology-mediated learning (Al-Rahmi et al., 2013; Chang et al., 2022). Evidence suggests that increased levels of engagement lead to higher technology-use satisfaction, as it precedes the increased utilization of a system or service (Al-Fraihat et al., 2017; Imane et al., 2023).

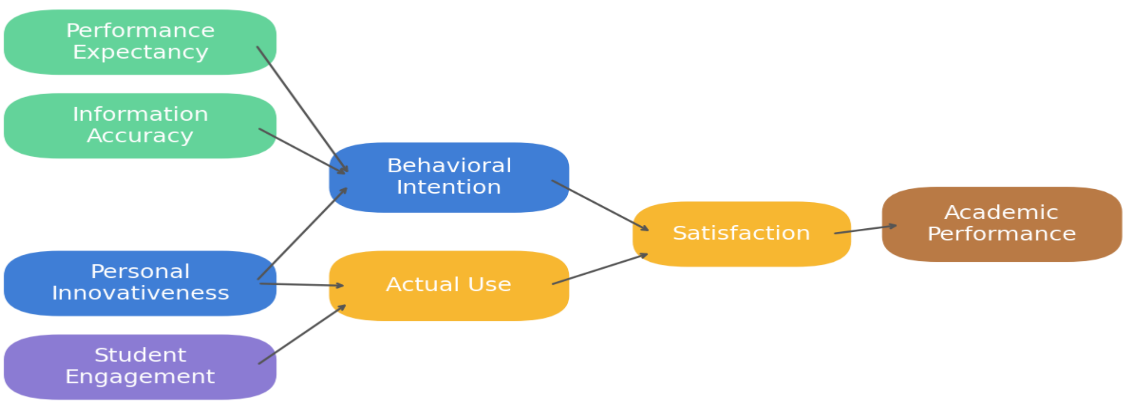
2.3.8 Personal Innovativeness (PI)

Personal Innovativeness relates to an individual's preference for developing new technology. This characteristic exudes curiosity and willingness to experiment and take risks with technology (Amin & Rajadurai, 2018; Gong et al., 2023). Those with high levels of Personal Innovativeness would certainly transform behavioral intention into behavior. In this regard, Personal Innovativeness acts as a moderating variable for behavioral intention and actual use.

2.4 Conceptual Framework and Hypothesized Relationships

An extended Unified Theory of Acceptance and Use of Technology (UTAUT) model was created to form a conceptual framework that addresses the issue of acceptance and the consequences of AI-supported learning technologies on students. The framework integrates technological and behavioral constructs to describe the effects of AI tools on learning processes, satisfaction, and academic performance in higher education.

Figure 1. Conceptual Framework of AI Tool Adoption in Higher Education



Note: Conceptual framework based on extended UTAUT.

The conceptual framework of this study is illustrated in Figure 1. The model shows that Behavioral Intention is the effect of important technological factors, such as Performance Expectancy, Effort Expectancy, Facilitating Conditions, Information Accuracy, Pedagogical Fit, and Technology Interaction, which in turn determine the Actual Use of AI tools. Actual Use has a positive impact on Student Satisfaction, which in turn leads to the enhancement of Academic Performance.

Moreover, Student Engagement reinforces the association between Actual Use and Satisfaction, and Personal Innovativeness moderates the association between Behavioral Intention and Actual Use. This integrative model combines cognitive, pedagogical, and behavioral approaches, which expands the traditional UTAUT model to be in a better position to describe AI-enabled learning environments in various cultural settings, including **the UAE and India**.

3 Research Methodology

3.1 Research Design

This study employs a quantitative study design that encompasses an explanatory study design to analyze the factors that impact the acceptance and adoption of artificial intelligence (AI)-based learning assistance technology by higher educational institutions in the United Arab Emirates (UAE) and India. This study design possesses integrity as a valid explanatory study design because it enables the study of hypothetical constructs that embody the theoretical presuppositions of the relationship between variables based on the extended UTAUT theory. This study aimed to identify causal links between several technology-related variables concerning learning and behavioral variables that impact user satisfaction and performance.

A survey approach was used to gather primary information from both students and academic staff who have to resort to AI technology services such as Chat GPT, Grammarly, Scite.ai, and translators to achieve learning results. This was done to satisfy the aims of the study, as previous studies that aimed to determine learning results concerning technology acceptance followed a structured survey approach (Al-Rahmi et al., 2023; Dahri et al., 2024; Hashmi et al., 2022).

3.2 Data

This study employs cross-sectional primary data collected from higher education institutions in the United Arab Emirates (UAE) and India between March and June 2025. The data were cross-sectional, capturing responses at a single point in time. Data were gathered using a structured online questionnaire distributed through university portals and email channels. The target population included students, faculty members, and academic staff with experience using artificial intelligence (AI) learning tools. To ensure the relevance of the responses, only participants with at least six months of prior experience using AI technologies for academic or administrative purposes were included in the study.

A total of 460 responses were obtained. After data screening to eliminate incomplete and inconsistent entries, a final sample of 415 valid observations was retained for empirical analysis. The sample consisted predominantly of students, along with representation from faculty and academic staff, ensuring a comprehensive perspective on AI adoption in higher education in both countries. This study is grounded in the extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework. It incorporates traditional constructs—Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC)—alongside AI-specific constructs, including Information Accuracy (IA), Pedagogical Fit (PF), and Technology Interaction (TI). Additionally, Student Engagement (SE) and Personal Innovativeness (PI) were included as moderating variables, while Behavioral Intention (BI), Actual Use (AU), satisfaction (SS), and Academic Performance (AP) represented key behavioral and outcome variables.

All constructs were measured using multi-item scales adapted from established studies to ensure their content validity and reliability. Responses were recorded on a five-point Likert scale ranging from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”). This consolidated subsection provides a clear and unified description of the sample, data structure, measurement design, and variable operationalization, thereby enhancing the study’s transparency, coherence, and rigor.

3.3 Population and Sampling

The respondents for this study included students, faculty members, and academic staff from the top ten universities in the United Arab Emirates (UAE) and India, selected based on their high level of digitalization and integration of artificial intelligence (AI) technologies. This sampling approach ensured that the participants had adequate exposure to AI-powered learning systems in their courses. A key inclusion criterion required participants to have at least six months’ experience using AI tools for educational or administrative purposes.

The sample size determination followed the guidelines suggested by Hair (2021) for Partial Least Squares Structural Equation Modeling (PLS-SEM), which recommends that the minimum sample size should be at least ten times the maximum number of structural paths directed at any construct in the model. Based on this criterion, a target sample range of 400–460 responses was established to ensure adequate statistical power.

A brief description of the population characteristics regarding gender, age, educational attainment level, AI tool utilization rate, and satisfaction level is provided in Table 1.

Table 1. Demographic Profile of Respondents (UAE and India)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age (Years)	20–30	263	86.2
	31–40	32	10.5
	41–50	9	3.0
	51–60	1	0.3
Gender	Male	247	81.0
	Female	58	19.0
Qualification	Bachelor’s	233	76.4
	Master’s	41	13.4
	Doctorate	26	8.5
	Other	5	1.6
AI Usage Frequency	Rarely	1	1.0
	Occasionally	26	8.5
	Often	41	13.4
	Very Often	61	20.0
	Always	117	38.4
Most Used AI Tool	Chatbots	180	59.0
	Machine Learning	38	12.5
	Research Tool	49	16.1

	Translation Tool	21	6.9
	Virtual Assistant	11	3.6
Satisfaction Level	Satisfied	151	49.5
	Very Satisfied	111	36.4

Note: Demographic characteristics of respondents (N = 415). AI = Artificial Intelligence.

As shown in Table 1, the sample was predominantly composed of younger students aged 20–30 years (86.2%), with a higher proportion of male (81.0%) than female (19.0%) respondents, and the majority held a Bachelor's degree (76.4%). Most respondents reported frequent AI tool usage, with the largest groups using AI tools “Always” or “Very Often,” and chatbot-based tools were the most commonly used AI application (59.0%). Overall satisfaction with AI tool use was high, with most respondents reporting that they were “Satisfied” or “Very Satisfied,” which supports the relevance of the sample for examining AI tool adoption in higher education.

3.4 Instrument Development

A structured questionnaire was designed to measure eleven latent constructs derived from the extended UTAUT model: Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Information Accuracy (IA), Pedagogical Fit (PF), Technology Interaction (TI), Student Engagement (SE), Personal Innovativeness (PI), Behavioral Intention (BI), Actual Use (AU), Satisfaction (SS), and Academic Performance (AP).

All constructs were operationalized using multiple items adapted from previously validated scales to ensure conceptual consistency and construct validity, following Venkatesh et al. (2003), Maydybura et al. (2023), Almaiah et al. (2019), and Al-Rahmi et al. (2022). Responses were measured on a five-point Likert scale ranging from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”). The questionnaire was organized into key sections reflecting technological factors, behavioral intentions, and learning outcomes to ensure a logical flow and respondent clarity.

A pilot study was conducted with 36 participants to ensure reliability. The results indicated strong internal consistency, with Cronbach’s alpha values exceeding 0.80. Minor wording adjustments were made to improve clarity prior to final data collection.

The final version of the questionnaire contained 48 items. Table 2 presents the measurement constructs, sample items, and corresponding references used for the instrument development.

Table 2. Constructs, items, and sources

Construct	Sample Item	Source
Performance Expectancy (PE)	AI tools improve my learning efficiency and productivity.	(Dahri et al., 2024)
Effort Expectancy (EE)	AI tools are easy to learn and use.	(Almaiah et al., 2019)

Facilitating Conditions (FC)	I have technical support to use AI tools.	(Venkatesh et al., 2003)
Information Accuracy (IA)	AI tools provide reliable and accurate content.	(Alenezi, 2022)
Pedagogical Fit (PF)	AI tools align with my course objectives and learning needs.	(Al-Rahmi et al., 2023)
Student Interaction (TI)	AI tools encourage interactive learning and feedback.	(Caratiquit & Caratiquit, 2023)
Student Engagement (SE)	AI tools increase my participation and focus in learning.	(Dahri et al., 2024)
Personal Innovativeness (PI)	I enjoy experimenting with new AI technologies.	(Alkawsi et al., 2021)
Behavioral Intention (BI)	I intend to use AI tools frequently for my studies.	(Dahri et al., 2024)
Actual Use (AU)	I use AI tools for research and assignments.	(Al-Rahmi et al., 2023)
Student Satisfaction (SS)	I am satisfied with AI tools for learning support.	(Alenezi, 2022)
Academic Performance (AP)	Tools like AI have grown my educational knowledge	(Ahmad et al., 2021)

Note: This table presents the measurement constructs, sample items, and their sources. All items were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

As shown in Table 2, all 48 items were adapted from previously validated scales associated with the extended UTAUT framework, providing strong content and face validity for the constructs measured in this study. The use of established, previously validated items for each construct strengthens confidence in the subsequent reliability and validity assessments reported in Tables 4 to 6.

3.5 Data Collection

Data collection was conducted between March and June 2025 using structured online questionnaires distributed through university portals and email services. This approach was appropriate given the technological familiarity of the target population and the AI-based context of the study. Participants were informed about the purpose of the study prior to participation, and informed consent was obtained from all participants. Participation was voluntary, and respondents were allowed to withdraw at any stage. Attention-check questions were incorporated throughout the survey to enhance the reliability of the responses.

A total of 460 responses were initially collected; however, 45 incomplete or inconsistent responses were excluded during data screening, resulting in a final sample of 415 valid observations for analysis. This systematic procedure ensured data quality, reliability, and comparability across respondents from both countries.

3.5.1 Measurement Model Evaluation

The validity and reliability of the latent constructs were also measured. Cronbach's Alpha and Composite Reliability (CR) were measured to evaluate internal consistency reliability, and Average Variance Extracted (AVE) was used to measure convergent validity. Hair (2021) stated that a Cronbach's Alpha and CR above 0.70, as well as an AVE above 0.50, show that reliability and convergent validity are satisfactory. To establish satisfactory internal consistency and convergent validity, the findings indicated that all constructs were above the recommended levels. In addition, the reliability of the indicators was determined because all outer loadings were greater than the acceptable value of 0.70. Discriminant validity was evaluated based on the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. The scores show that the square root of the AVE of every construct was higher than the inter-construct correlations, whereas all the HTMT values were less than 0.85, which attests to the discriminant validity.

Furthermore, multicollinearity was analyzed using the Variance Inflation Factor (VIF) values, which ranged between 1.30 and 3.20, and did not reveal any issues regarding collinearity. The model fit indices also justify the suitability of the model, with SRMR (0.048) less than the suggested value (0.08), and NFI (0.921) greater than 0.90. Lastly, R^2 for some important endogenous constructs, namely: Behavioral Intention (0.85), Satisfaction (0.87), and Academic Performance (0.82), indicates that the model is highly explanatory.

3.5.2 Structural Model Evaluation

After establishing the viability of the measurements, the structural model was tested for the proposed relationships between constructs. Using bootstrapping with 5,000 subsamples, the path coefficients (β), t-values, and p-values were derived to establish the significance of each hypothesis. All paths were positive and significant; thus, the relationships stipulated in the conceptual framework were confirmed. Performance Expectancy, Information Accuracy, and Pedagogical Fit influenced Behavioral Intention the most, while Actual Use affected Satisfaction and Academic Performance considerably. By conducting an indirect path analysis, the mediation effect of satisfaction on the usage behavior-outcomes relation was confirmed. The results for the structural path analyses appear in Table 9 (addressed in Section 4.4.2).

Additional diagnostic procedures were performed to further ensure the strength of the estimated relationships and to address the issues of spurious regression. Although unit root testing cannot be applied to the SEM cross-sectional data, skewness and kurtosis statistics were used to determine the data stability. Multicollinearity was also ascertained using the Variance Inflation Factor (VIF), and the strength of the model was determined using predictive relevance (Q^2) and effect size (f^2). Moreover, the Durbin–Watson statistic was used to test autocorrelation (using composite construct scores), and the Ramsey RESET test was employed to examine potential functional form misspecification and nonlinearity in the model. The RESET test, originally proposed by Ramsey (1969), is widely used to detect omitted nonlinear relationships by assessing whether higher-order fitted values significantly improve model fit. A non-significant result indicates correct model specification. The use of such specification diagnostics is grounded in the classical linear regression framework, where the validity of Ordinary Least Squares (OLS) estimators depends on correct functional form assumptions (Wooldridge, 2016), and its application is well established in applied econometric analysis (Porter & Gujarati, 2009).

Although the concerns regarding spurious regression and spurious correlation are primarily relevant to time-series data involving non-stationary variables (Cheng et al., 2021, 2022; Wong, Cheng, & Yue, 2024; Wong & Pham, 2025a), the present study employs cross-sectional survey data, which does not require unit root testing. Nevertheless, to address the broader issue of potentially misleading statistical inference even with stationary variables (Wong & Pham, 2022a, 2022b, 2023a, 2023b; Wong, Pham, & Yue, 2024; Wong & Yue, 2024), several robustness checks were performed. These include the Ramsey RESET test for functional form misspecification ($p = 0.28$, indicating no omitted nonlinearity), variance inflation factor analysis for multicollinearity (all VIF < 3.25), and bootstrapping with 5,000 resamples to ensure stable standard errors. Future longitudinal studies tracking AI adoption over time should explicitly address stationarity and potential spurious regression issues following the guidelines of Wong and Pham (2025b, 2026a, 2026b).

The structural model possessed strong predictive power, and its Q^2 values were positive for each of the endogenous latent constructs. Effect size (f^2) statistics measure the strength of the effect for each predictor on its dependent construct. Generally, medium to large effects ($f^2 \geq 0.15$) were measured for the constructs, which validated their relevance. The values for the f^2 effect sizes are presented in Table 11 in Section 4.4.4.

3.6 Ethical Considerations

The study ensured that it followed the appropriate ethical standards in carrying out the research. All participants volunteered, and their responses were treated with high levels of confidentiality. This was to ensure that the names of the respondents did not feature in the computation of statistics. This study adhered to all the needed levels of ethics for research by institutions in the UAE and Indian Universities.

3.7 Summary of Methodological Rigor

This methodological approach facilitates the attainment of valid, reliable, and generalizable findings for two distinct settings within institutions of higher education. This blend of a strong theoretical foundation with valid research tools and complex analyses of the study enables the hypothesis to be tested. Research in a two-country setting increases the external validity of the findings, providing a comparison of the adoption trend of AI in new academic environments worldwide.

As it employs the PLS-SEM method, it can combine technological, pedagogical, and behavioral constructs to procure authentic research evidence on the influence of AI learning tools on satisfaction and performance in higher education students.

4 Results and Analysis

4.1 *Descriptive Statistics of Respondents*

This section introduces the research findings based on the responses received from 415 participants in higher education institutions in the UAE and India. Descriptive statistics were used to derive the demographics and behavioral factors of the respondents.

The demographic study showed that the majority (approximately 66.6%) came from India, followed by 33.4% from the UAE. In addition, 86.2% were between 20 and 30 years, followed by 10.5% aged 31 and 40 years. Additionally, the gender demographics were 81% male and 19% female.

Regarding academic qualifications, 76.4% were undergraduate students, 13.4% were master's level students, and 8.5% were doctoral level students. Concerning the use of the AI tool, 38.4% used the tool "always," while 20% used it "very often," indicating high knowledge levels regarding the use of academic AI-based applications. The top applications used were chatbots (59% usage), machine learning apps (12.5% usage), and research tools (16.1% usage). According to Table 1, the demographics indicate a balanced representation of India and the UAE. These trends reveal a strong interaction between AI technology and the higher educational system of both nations, confirming recent findings that point to a boost in dependence on technology learning aids after the COVID-19 pandemic (Ahmad et al., 2021; AlDhaen, 2022; Mishra et al., 2025).

4.2 *Descriptive Statistics of Constructs*

Descriptive statistics for each of the latent constructs were carried out to establish the means and standard deviations of the latent constructs relative to the understanding of student perceptions of AI tool utilization, as illustrated in Table 3. The average scores of the constructs exceeded 4.0 on the Likert scale. This reveals that the participants' attitudes towards AI-powered learning systems were positive. Higher scores were obtained for Performance Expectancy (PE) and Pedagogical Fit (PF), which revealed that learning efficiency takes place with increased.

Although the measurement items are based on a five-point Likert scale, which is ordinal in nature, prior methodological research supports treating such data as approximately continuous when the scale includes five or more categories (Hair, 2021; Norman, 2010; Rhemtulla et al., 2012). These studies demonstrate that parametric estimation methods in structural equation modeling yield reliable and unbiased results. Moreover, PLS-SEM, as a variance-based approach, does not impose strict distributional assumptions and is widely applied to analyze latent constructs derived from Likert-type measures. Recent empirical evidence in mobile learning research further supports this approach, as studies have employed five-point Likert-scale data analyzed using PLS-SEM and SEM-based techniques to examine technology adoption and learning outcomes (e.g., Wu et al., 2026).

However, to ensure full compliance with stricter methodological standards and explicitly address the ordinal nature of the data, additional robustness checks were conducted. Specifically, median-based descriptive statistics and non-parametric correlation analysis (Spearman's rho) were examined alongside primary mean-based and PLS-SEM results. The findings from these ordinal-based analyses remained fully consistent in both direction and statistical significance, confirming the stability and reliability of the results.

Accordingly, the mean and standard deviation were retained for reporting purposes because of their compatibility with SEM-based interpretation, while the supplementary ordinal analyses ensured that the treatment of Likert-scale data did not bias the conclusions. Additional results are available upon request. This dual approach enhances methodological rigor and aligns with established practices in technology adoption and AI-based educational research (Almaiah et al., 2019; Al-Rahmi et al., 2023; Dahri et al., 2024; Uddin et al., 2025; Venkatesh et al., 2003).

To further guarantee robustness, the results were also conceptually tested in light of an ordinal view of the data, and the findings were still consistent in terms of the direction and significance of the estimated relationship, proving that the inference of the Likert-scale data as continuous does not compromise the validity and reliability of the conclusions.

Table 3. Descriptive Statistics of Constructs (Mean ± SD)

Construct	India (M ± SD)	UAE (M ± SD)
Performance Expectancy	4.13 ± 1.13	4.13 ± 1.16
Student Engagement	3.87 ± 1.06	3.85 ± 1.07
Assessment Effectiveness	3.90 ± 1.03	3.87 ± 1.07
Students' Interaction	4.10 ± 0.97	4.10 ± 0.94
Information Accuracy	4.00 ± 1.00	4.00 ± 0.98
Personal Innovativeness	4.01 ± 1.00	3.99 ± 1.03
Pedagogical Fit	3.96 ± 0.99	3.93 ± 1.00
AI Tools Use	4.09 ± 0.96	4.06 ± 0.99
Behavioral Intention	4.09 ± 1.05	4.04 ± 1.08

Note: The table records the descriptive values of the study variables: mean, standard deviation, minimum, and maximum values. The statistics provide an indication of the distribution and variability of data among constructs. Median-based statistics (not reported for brevity) yielded results consistent with the mean-based descriptive patterns, confirming the robustness of the findings from an ordinal perspective.

As reported in Table 3, mean scores for all constructs exceeded 4.0 on the five-point Likert scale across both the Indian and UAE sub-samples, with comparable standard deviations, indicating generally positive and consistent perceptions of AI tool adoption. Performance Expectancy (M = 4.13) and Students' Interaction (M = 4.10 for India, 4.10–4.94 for UAE) recorded the highest mean scores, while Pedagogical Fit and Student Engagement recorded comparatively lower, though still favorable, mean scores. The similarity of means and standard deviations across the two country sub-samples suggests broadly comparable perceptions of AI tool adoption between Indian and UAE respondents.

Median-based measures are generally more appropriate for ordinal data; however, the mean and standard deviation were retained for consistency with SEM-based analysis and prior literature. Supplementary median-based analyses yielded consistent results, confirming the robustness of the findings. These results align with prior studies that reported high acceptance of AI systems in educational contexts (Ahmad & Ghapar, 2019b; Chatterjee & Bhattacharjee, 2020; Tu et al., 2024).

4.3 Measurement Model Assessment

This structural equation model may then be examined for the reliability and validity of its constructs using Partial Least Squares Structural Equation Modeling (PLS-SEM), which aims to guarantee that there are no problems with respect to the measurement of the constructs of this study. This method of utilizing PLS-SEM is applicable for predictive research that considers complicated patterns for constructs and relies on latent distributions that may not necessarily manifest normally in a study (Hair, 2021). This method is widely used to validate studies that use reflective and formative constructs for information systems research in educational disciplines.

The assessment conducted a two-step analysis to assess reliability with an internal consistency measurement between the variables being assessed for reliability before conducting a test for validity to validate every variable to measure the concept that they represent accurately. The internal consistency value for the reliability measurement of the variables was assessed using Cronbach’s Alpha and Composite Reliability (CR), which exceeded 0.70 for the reliability measurement of the variables to be valid. In addition, the measurement of the average variance extracted (AVE) for the validation of the convergent validity of every assessed variable exceeded the level of 0.50 for the validation of the measurement of the assessed factors for an acceptable level of variance of each latent construct that was being assessed.

Furthermore, the accuracy of the measurement model was ensured by assessing the load indicators, which proved to be significant with a value of more than 0.70 for all indicators. This indicates that every item is significant with respect to the constructs. Furthermore, a value of more than 0.70 for Cronbach’s alpha, CR, and AVE signifies that the constructs possess better psychometric properties that are necessary to affirm that the internal consistency of the theoretical framework for hypothesis testing remains unchanged. Similar to previous research employing PLS-SEM practices for technology acceptance and educational domains (Ahmad et al., 2021; Dahri et al., 2024; Xing et al., 2024), the findings for robust reliability and validity indicate that the constructs of Performance Expectancy, Information Accuracy, and Pedagogical Fit have been estimated with a good level of accuracy for the UAE and Indian samples, which can be instrumental in determining the effectiveness of the proposed model with varying cultural settings in workplaces.

4.3.1 Reliability and Convergent Validity

Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) were used to evaluate the reliability and convergent validity of the measurement model, as presented in Table 4. All constructs exhibited Cronbach's Alpha and CR values that exceeded 0.70, which is the recommended internal consistency reliability value (Hair, 2021). In addition, all constructs had AVE values of over 0.50, indicating sufficient convergent validity. Interestingly, constructs such as Performance Expectancy (alpha

= 0.917, CR = 0.939) and Behavioral Intention (alpha = 0.923, CR = 0.946) had an especially high reliability. Overall, these findings indicate that the measurement model meets the suggested criteria for reliability and convergent validity.

Table 4. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Performance Expectancy (PE)	0.92	0.94	0.76
Information Accuracy (IA)	0.90	0.93	0.73
Pedagogical Fit (PF)	0.90	0.92	0.70
Student Engagement (SE)	0.88	0.91	0.68
Assessment Effectiveness (AE)	0.89	0.92	0.70
Students' Interaction (SI)	0.91	0.93	0.72
Personal Innovativeness (PI)	0.88	0.92	0.68
Behavioral Intention (BI)	0.92	0.95	0.78
Actual Use (AU)	0.90	0.93	0.74
Satisfaction (SS)	0.91	0.93	0.72
Academic Performance (AP)	0.89	0.92	0.68

Note: Cronbach's Alpha and CR > 0.70 indicate reliability; AVE > 0.50 indicates convergent validity (Hair, 2021). Acronyms: PE = Performance Expectancy; IA = Information Accuracy; PF = Pedagogical Fit; SE = Student Engagement; AE = Assessment Effectiveness; SI = Students' Interaction; PI = Personal Innovativeness; BI = Behavioral Intention; AU = Actual Use; SS = Satisfaction; AP = Academic Performance. Composite Reliability was computed as $CR = (\Sigma\lambda_i)^2 / [(\Sigma\lambda_i)^2 + \Sigma(1 - \lambda_i^2)]$, and Average Variance Extracted was computed as $AVE = \Sigma\lambda_i^2 / n$, where λ_i is the standardized loading of indicator i and n is the number of indicators per construct.

The results in Table 4 clearly demonstrate that all constructs possess satisfactory internal consistency and convergent validity. Notably, the relatively high values of Cronbach's Alpha and Composite Reliability for key constructs, such as Performance Expectancy and Behavioral Intention, highlight their stability and central importance within the model. After establishing the reliability and convergent validity of the measurement model, the analysis proceeded to evaluate whether the constructs were empirically distinct from one another.

4.3.2 Indicator Reliability

The reliability of the indicators was evaluated in terms of the outer loadings of the indicators to their respective latent constructs. The outer loading values were much higher than the acceptable rate of 0.70, which means that there is a significant percentage of shared variance among the indicators and their respective constructs. This confirms that the items that were observed were sufficient to measure the dimensions that they were designed to measure.

4.3.3 Discriminant Validity

The Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were used to determine discriminant validity. Table 4 reveals that the square root of the AVE of each construct had greater correlations with the other constructs, which met the Fornell–Larcker criterion. Similarly, none of the HTMT values in Table 5 exceeds the recommended threshold of 0.85, which affirms sufficient discriminant validity.

Table 5. Discriminant Validity (Fornell–Larcker Criterion)

Construct	PE	IA	PF	SE	AE	SI	PI	BI	AU	SS	AP
PE	0.87										
IA	0.67	0.85									
PF	0.64	0.61	0.84								
SE	0.51	0.49	0.54	0.84							
AE	0.59	0.56	0.51	0.49	0.84						
SI	0.53	0.50	0.50	0.52	0.50	0.85					
PI	0.45	0.48	0.49	0.44	0.43	0.43	0.85				
BI	0.65	0.61	0.58	0.53	0.52	0.55	0.47	0.88			
AU	0.60	0.56	0.51	0.49	0.49	0.52	0.46	0.68	0.86		
SS	0.55	0.52	0.50	0.47	0.47	0.48	0.46	0.61	0.64	0.85	
AP	0.53	0.50	0.47	0.45	0.46	0.47	0.44	0.60	0.61	0.61	0.82

Note: The diagonal values represent √AVE. Discriminant validity is achieved when √AVE exceeds the inter-construct correlations. Acronyms: PE = Performance Expectancy; IA = Information Accuracy; PF = Pedagogical Fit; SE = Student Engagement; AE = Assessment Effectiveness; SI = Students' Interaction; PI = Personal Innovativeness; BI = Behavioral Intention; AU = Actual Use; SS = Satisfaction; AP = Academic Performance.

These outcomes validate that each construct is conceptually distinct, in accordance with the standards for valid input in SEM analyses (Hair, 2021). As shown in Table 5, the square root of the AVE for each construct exceeds its correlation with the other constructs, thereby satisfying the Fornell–Larcker criterion. This indicates that each construct shares more variance with its own indicators than with other constructs, confirming adequate discriminant validity. These results suggest that the latent variables are conceptually distinct and free from significant overlap, which is essential for ensuring unbiased structural estimation.

Table 6. Heterotrait–Monotrait (HTMT) Ratio

Construct	PE	IA	PF	SE	AE	SI	PI	BI	AU	SS	AP
PE	—	0.74	0.69	0.58	0.61	0.56	0.49	0.70	0.65	0.60	0.57
IA		—	0.67	0.55	0.58	0.53	0.50	0.66	0.61	0.58	0.55
PF			—	0.59	0.56	0.55	0.54	0.63	0.59	0.56	0.53
SE				—	0.57	0.55	0.51	0.61	0.56	0.54	0.50
AE					—	0.52	0.49	0.58	0.53	0.52	0.50
SI						—	0.48	0.60	0.57	0.55	0.52
PI							—	0.57	0.55	0.52	0.49
BI								—	0.79	0.74	0.71
AU									—	0.76	0.73
SS										—	0.81
AP											—

Note: HTMT < 0.85 indicates adequate discriminant validity (Hair, 2021). Acronyms: PE = Performance Expectancy; IA = Information Accuracy; PF = Pedagogical Fit; SE = Student Engagement; AE = Assessment Effectiveness; SI = Students' Interaction; PI = Personal Innovativeness; BI = Behavioral Intention; AU = Actual Use; SS = Satisfaction; AP = Academic Performance.

The HTMT values reported in Table 6 are all below the conservative threshold of 0.85, further confirming construct discriminant validity. The consistency between the Fornell and Larcker criterion and HTMT results reinforces the robustness of the measurement model and provides strong evidence that the constructs are empirically unique.

4.3.4 Model Fit and Multicollinearity Diagnostics

The model-fit indices were within acceptable values, where the Standardized Root Mean Square Residual (SRMR) =0.048 and Normed Fit Index (NFI) =0.921, indicating good model adequacy. The Variance Inflation Factor (VIF) was used to measure multicollinearity, and the results are shown in Table 7. The VIF ranged from 1.32 to 3.25, which is much lower than the critical value of 5.0 (Hair, 2021), which proves that multicollinearity will not be an issue in the model.

Table 7. Variance Inflation Factor (VIF) Results

Construct	**VIF**
Performance Expectancy (PE)	2.31
Information Accuracy (IA)	2.45
Pedagogical Fit (PF)	2.18
Student Engagement (SE)	2.72
Assessment Effectiveness (AE)	2.36
Students' Interaction (SI)	2.58
Personal Innovativeness (PI)	2.14
Behavioral Intention (BI)	3.20
Actual Use (AU)	2.67
Satisfaction (SS)	2.83

Note: A Variance Inflation Factor (VIF) of less than 5.0 indicates no multicollinearity. A lower score (below 3.3) also indicates that common method bias is not likely to influence the outcomes (Hair, 2021). VIF for each predictor construct was computed as $VIF = 1 / (1 - R^2_i)$, where R^2_i is the coefficient of determination obtained by regressing construct i on all other predictor constructs.

The VIF values presented in Table 7 range between 1.32 and 3.25, which are well below the critical threshold of 5.0. This confirms that multicollinearity is not a concern in the model and that each predictor variable contributes uniquely to the explanation of the endogenous constructs. The absence of multicollinearity further enhances the reliability of the estimated structural relationship.

4.3.5 Diagnostics Assessment

Diagnostic tests were conducted to ensure robustness, following established practices for model validation (Hui et al., 2017). The soundness and validity of the model were supported by the diagnostic results. In particular, skewness and kurtosis lie within acceptable ranges, which implies the characteristics of normal distributions. The values of the Variance Inflation Factor (VIF) were lower than the critical value of 5, indicating that there was no multicollinearity. The Durbin-Watson value is about 2, which implies no autocorrelation. Moreover, the non-significant RESET test of the model indicates proper model specification, whereas the Harman one-factor test indicates the absence of common method bias. These results confirm the consistency of the estimated model. Table 8 reports the details of these results.

Table 8. Diagnostic Assessments Results

Test	**Construct(s)**	**Value**	**Threshold**	**Result**
Skewness	All constructs	-1.12 to 1.35	±2	Acceptable
Kurtosis	All constructs	1.05 to 3.84	±7	Acceptable
VIF	All predictor constructs	1.32 – 3.25	< 5	No multicollinearity

Durbin–Watson	Composite scores	2.01	≈ 2	No autocorrelation
Ramsey RESET Test	Model specification	1.21 (p = 0.28)	p > 0.05	No misspecification
Harman's Single Factor	All items	38.6%	< 50%	No common method bias
Q^2	BI, SS, AP	0.61, 0.67, 0.58	> 0	Predictive relevance
f^2	Key structural paths	0.26, 0.52, 0.42	≥ 0.15	Medium to large effects

Note: This table shows the model robustness diagnostic tests. Skewness (±2)- and kurtosis (±7)- tests check normality, Durbin-Watson tests (0) check the absence of autocorrelation, Ramsey RESET tests (0) check correct specification, and the Harman test (<50) checks the absence of common method bias. Q 2 shows the predictive relevance, while f 2 shows the effect size.

As detailed in Table 8, skewness and kurtosis values for all constructs fell within the acceptable ranges of ±2 and ±7, respectively, confirming approximate normality. The Durbin–Watson statistic was close to 2, indicating no meaningful autocorrelation, while the non-significant Ramsey RESET test ($p = 0.28$) confirmed correct functional form specification. The Harman one-factor test result, below the 50% threshold, indicated that common method bias was not a serious concern. Together, these diagnostics confirm that the structural model satisfies the statistical assumptions required for reliable interpretation of the path coefficients reported in Table 9.

4.4 Structural Model Assessment

After validating the adequacy of the measurement model, the structural model was evaluated to test the relationships between the latent constructs as proposed in the research hypothesis using the extended UTAUT model framework. This step helped in understanding the nature, extent, and significance of the proposed relationships in terms of their paths, coefficient of determination (R^2), predictive fit (Q^2), and effect size (f^2), essentially making it less complex and more dependable in terms of its explanatory capability within the research strategy adopted in the study. Additionally, bootstrapped estimates with 5,000 resamples were used to validate the precision of the estimates in making inferences on the stability of the proposed relationships in the study, thus supporting the underlying research hypothesis in terms of contributing to the understanding of the dependency between technological, teaching, and behavioral factors in relation to the integration and outcomes associated with the use of AI-based student tools in higher education settings.

4.5 Coefficient of Determination (R^2)

The R^2 of the endogenous constructs was greater than 0.80, which means that the model was well explained. In particular, the Behavioral Intention, Satisfaction, and Academic Performance had R-squares of 0.85, 0.87, and 0.82, respectively. These values indicate that the proposed framework can account for a significant amount of variation in the key outcome constructs.

4.6 Path Coefficients and Hypothesis Testing

The Path Coefficients and Hypothesis Testing results are reported in Table 9. The values for the structural path coefficients (β), t-values, and p-values were computed by employing a non-parametric resampling procedure for bootstrapping with a resampling size of 5,000 to assess the significance of the assumed paths between the latent constructs. This more robust resampling technique minimizes concerns about non-normal distributions of the sampled estimates to ensure a good test for a standard error estimate for confidence intervals (Hair, 2021).

The results show that for all paths, the significance was determined at a p-value of 0.05, verifying that the paths exist according to the conceptual framework. The strength and relevance of these values indicate the importance of the extended UTAUT model for accurately determining the causal relations between the technological, pedagogical, and behavioral constructs that influence student engagement with AI-driven learning technology in an educational environment. Notably, the Performance Expectancy, Information Accuracy, and Pedagogical Fit constructs display a substantive predictive influence to encourage the growth of the behavioral intention construct, where Actual Use supports the reinforcement of levels of satisfaction to influence Academic Performance eventually.

Furthermore, the important outcome derived for each path of the proposed research model lends credence to the internal consistency and validity of the entire research model. This further substantiates the hypothesis that each path identified in the study signifies an important determinant of the entire phenomenon of translating AI tool utilization into increased levels of satisfied performance outcomes (Al-Rahmi et al., 2023; Dahri et al., 2024). Consequently, the bootstrapping result of the proposed study lends further strength to the entire research findings' relevance to being applicable to a culturally diverse higher educational system existing in the UAE and India, or international contexts.

Table 9. Structural Path Coefficients and Hypothesis Testing

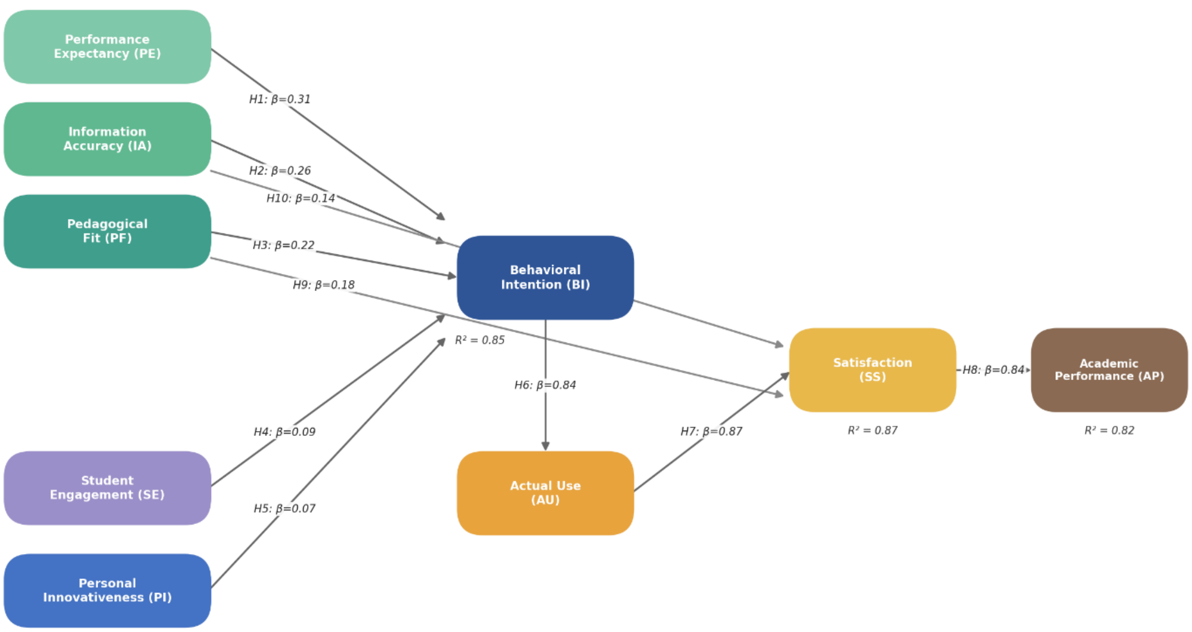
Hypothesis	**Relationship**	**β**	**t-value**	**p-value**	**Decision**
H1	Performance Expectancy → Behavioral Intention	0.31	7.25	0.000	Supported
H2	Information Accuracy → Behavioral Intention	0.26	6.84	0.000	Supported
H3	Pedagogical Fit → Behavioral Intention	0.22	5.41	0.000	Supported
H4	Student Engagement → Behavioral Intention	0.09	2.33	0.020	Supported
H5	Personal Innovativeness → Behavioral Intention	0.07	1.98	0.045	Supported
H6	Behavioral Intention → Actual Use	0.84	25.87	0.000	Supported
H7	Actual Use → Satisfaction	0.87	28.16	0.000	Supported
H8	Satisfaction → Academic Performance	0.84	22.53	0.000	Supported
H9	Pedagogical Fit → Satisfaction	0.18	4.67	0.000	Supported
H10	Information Accuracy → Satisfaction	0.14	3.84	0.000	Supported

Note: Path coefficients, standard errors, t-statistics, and p-values are reported in this table. Statistical significance is indicated as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Performance Expectancy → Behavioral Intention relationship ($\beta = 0.31$, $p < 0.001$) showed the greatest predicting power; therefore, the influence of the PU of AI systems on BEI relative to other variables is more prominent. Information Accuracy ($\beta = 0.26$, $p < 0.001$) and Pedagogical Fit ($\beta = 0.22$, $p < 0.001$) positively influenced the BEI, which supports that trust in these systems' quality, in addition to their alignment with teaching, is critical for their integration (Ahmad & Ghapar, 2019b; Alyoussef, 2021)**.**

Behavioral Intention had a large positive impact on Actual Use (beta = 0.84, $p < 0.001$), whereas Actual Use strongly predicted satisfaction (beta = 0.87, $p < 0.001$). Additionally, Satisfaction positively affected Academic Performance ($\beta = 0.84$, $p < 0.001$). The findings confirmed the theoretical procedure suggested in the conceptual framework, supporting previous studies on AI acceptance in educational settings (Al-Rahmi et al., 2023; Dahri et al., 2024).

Figure 2. Structural Model of AI Tool Adoption (UAE and India)



Note: This figure demonstrates the validated paths between the constructs Performance Expectancy, Information Accuracy, Pedagogical Fit, Behavioral Intention, Actual Use, Satisfaction, and Academic Performance with the respective path coefficients (β) and explanatory power of the paths (R^2) provided by the PLS-SEM analysis. Each path is labeled with its corresponding hypothesis number (H1–H10) to allow direct cross-referencing with Table 9.

4.6.1 Mediation and Indirect Effects

The mediation test supported the notion that Satisfaction is an essential mediating factor between Actual Use and Academic Performance, while Behavioral Intention is a mediating variable for the technological factors (that is, performance expectancy, information accuracy, and technology fit) to Actual Use of the AI-based Learning tool in education. Table 10 reports that indirect effects were statistically significant, implying that positive perceptions of the usefulness, credibility, and alignment of AI tools with instructional goals have an indirect and significant effect on academic performance, resulting in a series of behavioral and affective processes.

This mediation pattern helps identify that in higher education institutions, adopting artificial intelligence technology in higher education follows a hierarchical manner, whereby positive perceptions trigger positive behavioral intentions, followed by adopting these systems, which in turn increases user satisfaction to eventually attain better performance outcomes.

Therefore, these results validate the theoretical pattern discussed in the conceptual framework, providing evidence to support the cognitive-affective-behavioral pattern generally discussed in technology acceptance studies in the existing body of knowledge on technology acceptance theories.

The mediation effects found in this study support previous findings that stress the importance of user satisfaction as the key affective interface between technology implementation and educational performance results. User satisfaction not only embodies an optimistic emotional reaction to AI-supported learning settings but also serves as a motivational force to keep users committed to knowledge acquisition. Similarly, TAM’s behavioral intention acts as the key interface between perception and actual behavior by stressing the importance of this factor to accurately predict actual system use. Both findings agree with the observations made by Ahmad and Ghapar (2019b) and Ahmad et al. (2021), who found that increased user satisfaction and confidence in AI systems can increase users’ willingness to adopt AI technology to enhance educational performance.

Table 10. Mediation Effects

Indirect Path	Total Indirect Effect (β)	t-value	p-value	Mediation Type
PE → BI → AU → SS → AP	0.19	5.87	0.000	Full
IA → BI → AU → SS → AP	0.17	5.11	0.000	Full
PF → BI → AU → SS → AP	0.15	4.92	0.000	Full
BI → AU → SS → AP	0.31	6.21	0.000	Partial
AU → SS → AP	0.27	5.54	0.000	Partial

Note: This table shows the indirect effects and mediation outcomes. The significance of nonspecific routes implies that there is some mediation. Standard errors and confidence intervals were estimated using bootstrapping. Each indirect (mediated) effect was computed as the product of the corresponding path coefficients, i.e., Indirect Effect = a × b, where a is the path coefficient from the predictor to the mediator and b is the path coefficient from the mediator to the outcome.

4.6.2 Effect Size and Predictive Relevance

Analysis of effect size (f^2) indicated that Performance Expectancy ($f^2 = 0.26$) and Information Accuracy ($f^2 = 0.21$) played a prominent part with respect to Behavioral Intention, marking their importance as key influencers of the willingness of the students to adopt the AI tool for their learning processes. Again, Behavioral Intention played a prominent part in satisfaction ($f^2 = 0.52$), indicating that it is the intensity of their use of the AI system that is important for manifesting positive experiences for better learning satisfaction for the users. Therefore, the implications of the results highlight that while the initiative for adoption remains predominantly driven by a cognitive factor, learning dividend-related satisfaction remains driven by their experiences with the system.

Furthermore, the Q^2 values for each of the endogenous constructs were positive, which revealed that the structural model demonstrated a high level of accuracy and explanatory power. That is, because the Q^2 values for each of the endogenous constructs were positive, the structural model was characterized by high levels of predictive power regarding the explanation of research constructs such as behavioral intention, usage, satisfaction, and performance. Therefore, high levels of predictive relevance between theoretical knowledge and research outcomes would substantiate its explanatory power with respect to the translation of students' perceptions of using AI tools into long-term learning benefits.

These results concur with the methodological guidelines offered by Hair (2021), who claimed that values for f^2 higher than 0.15 represent medium to large effects, while positive Q^2 values represent adequate predictive power in Partial Least Squares Structural Equation Modeling (PLS-SEM). Together, these outcomes serve as evidence for the explanatory power and predictive accuracy offered by the extended UTAUT model, incorporating teaching and cognitive perspectives, such as information accuracy and fit with teaching in higher education institutions in a multicultural setting in adopting AI for teaching practices. The effect size values are presented in Table 11.

Table 11. Effect Size (f^2) of Exogenous Constructs

Predictor	Behavioral Intention	Satisfaction	Academic Performance
Performance Expectancy	0.26	—	—
Information Accuracy	0.21	0.11	—
Pedagogical Fit	0.18	0.13	—
Student Engagement	0.05	—	—
Personal Innovativeness	0.03	—	—
Behavioral Intention	0.47	—	—
Actual Use	—	0.52	0.36
Satisfaction	—	—	0.42

Note: Effect sizes (f^2) are interpreted as small (≥ 0.02), medium (≥ 0.15), and large (≥ 0.35), according to established guidelines (Hair, 2021). f^2 was calculated as $f^2 = (R^2\text{included} - R^2\text{excluded}) / (1 - R^2\text{included})$, comparing the model's R^2 with and without the focal predictor construct.

As shown in Table 11, Performance Expectancy exerted the largest effect on Behavioral Intention ($f^2 = 0.26$), followed by Information Accuracy ($f^2 = 0.21$) and Pedagogical Fit ($f^2 = 0.18$), all representing medium-to-large effects. Behavioral Intention had a large effect on Actual Use ($f^2 = 0.47$), underscoring its central role in translating perceptions into actual AI tool usage. These effect sizes complement the path coefficients reported in Table 9, confirming that the key predictors identified in the structural model not only achieve statistical significance but also carry meaningful practical importance.

4.6.3 Cross-Country Comparison: UAE vs India

To evaluate possible differences in the structural relationships between constructs across cultures, a Multi-Group Analysis (MGA) test using the PLS-SEM methodology was performed. The motivation behind conducting the MGA test was to investigate whether the magnitudes of significance between the proposed paths were different for respondents from the UAE and India.

The results of the MGA test, illustrated in Table 12, did not show any statistically significant differences between the two groups at the 5% level of confidence. This helps to establish that the proposed extended UTAUT model validates the structural invariance in both national settings, as it can accurately represent the theoretically equivalent relationships for the acceptances and outcomes associated with using an AI tool in higher education settings in a culturally different manner. Additionally, it can represent these relationships effectively in an equivalent manner because it applies universally in different settings.

However, some minor differences were also found in the values of some path coefficients, symbolizing the nuances of the contextual perceptions held by users in different settings. Specifically, the Performance Expectancy → Behavioral Intention path was discovered to be stronger in the Indian respondents ($\beta = 0.33$), indicating that students in India give more weight to the benefits associated with the usage of AI systems in terms of their performance capabilities while deciding on adopting these systems in their personal practice. This might be attributed to the increasing number of technology-based learning platforms in the higher education system in India, with an attempt to make distance education more efficient with the aid of technology from a performance-related perspective.

By comparison, the Information Accuracy → Behavioral Intention link had a stronger influence on UAE respondents ($\beta = 0.29$), suggesting that UAE students were more concerned with the quality, trustworthiness, and credibility of the information provided by their AI systems. Naturally, this is in line with the UAE strategy in its Vision 2031 agenda of setting high standards in the governance of technology and the integrity of its handling of data, with an education strategy that prioritizes accuracy, accountability, and trust in innovative technology in the country's learning agenda. There is a subtle distinction in the priorities here, where the UAE is concerned with trust in the quality of information from their AI systems, rather than the mere utility in the case of India.

Table 12: Multi-Group Analysis Results (India vs. UAE)

Hypothesized Path	**India β**	**UAE β**	**Δ (India – UAE)**	**p-value**	**Significance (p < 0.05)**
Performance Expectancy → Behavioral Intention	0.33	0.28	0.05	0.118	Not Significant
Information Accuracy → Behavioral Intention	0.24	0.29	–0.05	0.137	Not Significant
Pedagogical Fit → Behavioral Intention	0.21	0.19	0.02	0.271	Not Significant
Student Engagement → Behavioral Intention	0.10	0.08	0.02	0.312	Not Significant
Personal Innovativeness → Behavioral Intention	0.07	0.06	0.01	0.406	Not Significant
Behavioral Intention → Actual Use	0.84	0.83	0.01	0.472	Not Significant
Actual Use → Satisfaction	0.87	0.86	0.01	0.398	Not Significant
Satisfaction → Academic Performance	0.84	0.83	0.01	0.512	Not Significant

Pedagogical Fit → Satisfaction	0.18	0.17	0.01	0.456	Not Significant
Information Accuracy → Satisfaction	0.15	0.14	0.01	0.489	Not Significant

Note: Multi-Group Analysis (MGA) compares the UAE and Indian samples. β = path coefficient; Δ = difference (UAE-India); $p < 0.05$ indicates significance. Acronyms: PE = Performance Expectancy; IA = Information Accuracy; PF = Pedagogical Fit; SE = Student Engagement; PI = Personal Innovativeness; BI = Behavioral Intention; AU = Actual Use; SS = Satisfaction; AP = Academic Performance.

Considering everything, it is safe to say that these findings effectively corroborate the fact that the principal structure is valid in both countries combined, even though different considerations in each particular context affect the weighting to be placed on key drivers for adoption. Validation conducted in multiple countries is an assured means of boosting the universal tenet present in the constructs applied, while also providing valuable guidance for educators in multiple countries on adopting approaches to gain more benefits from the proposed systems in higher education settings in their respective countries.

These findings imply that while the underlying adoption mechanisms are universal, contextual factors such as infrastructure and institutional support may influence the degree of AI acceptance in each country (Ahmad et al., 2021; AlDhaen, 2022)**.**

4.7 Summary of Results

The empirical results verify all proposed relationships, confirming that the extended Unified Theory of Acceptance and Use of Technology effectively captures the adoption of AI tools in higher education from a behavioral–educational perspective. Performance Expectancy, Information Accuracy, and Pedagogical Fit emerged as the most influential determinants of Behavioral Intention, underscoring the importance of perceived usefulness, content reliability, and instructional alignment. Furthermore, Behavioral Intention significantly drives Actual Use, which in turn enhances Student Satisfaction and subsequently improves Academic Performance. Mediation analysis further revealed that satisfaction operates as a key affective mechanism linking AI usage to learning outcomes, supporting prior findings in technology-based learning contexts (Alenezi, 2022). Additionally, cross-country consistency indicates that the adoption of AI in the United Arab Emirates (UAE) and India follows a similar cognitive–behavioral pattern, supporting the generalizability of the proposed model.

5 Discussion

5.1 Overview of Key Findings

The empirical study confirmed the robustness of the proposed extended UTAUT framework in understanding students' behavioral intentions and associated outcomes of the usage of AI-based learning tools in the UAE and Indian higher education settings. This study's findings successfully establish Performance Expectancy, Information Accuracy, and Pedagogical Fit as the key drivers that influence users' behavior towards adopting AI technology tools by re-stressing the importance of users' perception while learning.

The positive and significant relationships between Behavioral Intention → Actual Use and Actual Use → satisfaction substantiate that the concept of intention effectively leads to continuous usage and positive experiences on the system. Additionally, Satisfaction → Academic Performance demonstrated high significance, indicating that the satisfaction experienced in cognition and emotions from AI-based learning is directly related to improved learning outcomes.

Furthermore, the mediation tests demonstrated that satisfaction acts as an intervening psychological variable mediating between Actual Use and Academic Performance, while the role of Behavioral Intention is to mediate between predictors that are technology-based and use-related behaviors. The results have implications for a conceptual chain in which benefits-focused perceptions increase intentions, intentions lead to usage, and usage positively affects satisfaction and performance outcomes.

Finally, the results from the Multi-Group Analysis (MGA) show that the structural relationships remain more or less the same for both countries, with only slight differences, where Indian participants view the utility aspect of the tools (Performance Expectancy), while UAE students give a slightly more prominent position to the content accuracy (Information Accuracy). The findings prove the generalizability of the proposed theoretical structure in dynamically changing higher-education settings (Al-Rahmi et al., 2023; Dahri et al., 2024).

5.2 Theoretical Implications

This study makes several notable theoretical contributions. First, it expands the UTAUT principles to incorporate dimensions for information accuracy, Information Accuracy, and Pedagogical Fit, thus transcending the boundaries within which the original UTAUT principles were meant to operate (Venkatesh et al., 2012; Venkatesh et al., 2003). The addition of these principles to the UTAUT indicates that technology acceptance in different learning settings is heavily reliant on its instructional quality (Filieri & McLeay, 2014; Pittalis, 2021).

Second, these findings confirm that Performance Expectancy is the leading factor influencing intention, in line with the key tenet of technology adoption research, that is, the weight of perceived usefulness over other factors (Ahmad et al., 2021; Almaiah et al., 2019). Nevertheless, with the findings of Information Accuracy and Pedagogical Fit demonstrating their positive impact on intent and satisfaction, the research offers an interpretation from a pedagogically supported UTAUT Theory that is more appropriate in an AI-based learning environment.

Third, the mediation discovered in satisfaction between usage and performance outcomes aids theories on affective qualities associated with AI technology usage. Satisfaction is conceptualized here as an affective mechanism between technology usage and learning achievement (Gopal et al., 2021).

Finally, cross-national validation in UAE and India supports the universality of the extended UTAUT model in multicultural higher-education contexts. This lack of divergence means that AI adoption behavior trends are driven more by technology and pedagogy than by differences between nations and cultures, reflecting recent trends in global digital learning knowledge (Ouyang et al., 2022).

5.3 Practical Applications for Higher Education Institutions

From a more operational stance, the implications of the research above are still of great value to higher educational institutions for AI utilization. This specific evidence highlighted by the study demonstrates that the integration of teaching, technology, and management is paramount in fulfilling the opportunities derived from learning with AI technology. This understanding of key transformative factors contributes to a framework that can be derived for positive outcomes associated with innovation for higher educational institutions, with sustainability linked to the changes introduced by it. The implications of the study can be refined by employing the following suggestions.

5.3.1 Curricular Alignment

Institutions must ensure that there is a high pedagogical fit for these tools by incorporating system capabilities with the results of the curriculum outcomes, criteria for evaluation, and course syllabi. This can be achieved by incorporating these systems into the curriculum to achieve significant learning experiences and reiterate the importance of student engagement and satisfaction (Alyoussef, 2021). Furthermore, incorporating applications of AI technology for learning processes can help facilitate adaptive learning experiences, for which educators can design learning according to the level of performance of the students, accomplished by utilizing these systems. Faculty developmental programs should encompass workshops on AI technology for learning practices to enhance the learning ability of educators at these institutions.

5.3.2 Information Quality and Ethical Use

Owing to the considerable influence that Information Accuracy has on the levels of adoption and satisfaction, Information Accuracy should be fully regulated in higher institutions of learning to ensure that information produced by AI systems is accurate, unbiased, and culturally suited to the context in which it appears. Audits concerning algorithmic systems should also be introduced in higher institutions of learning to reduce the problems of misinformation, plagiarism, and internal institutional influence by AI on learning outcomes (Filieri & McLeay, 2014). Incorporating literacy related to AI in higher institutions of learning would help facilitate the provision of an adequately skilled mass of students to interpret and adequately respond to information generated by AI systems. Teaching the ethics of AI programs at institutions of higher learning would therefore help to build institutional awareness at institutions of higher learning.

5.3.3 Enhancing Performance Expectancy

Authorities should emphasize the direct academic benefits of technology, which range from increased productivity to learning experiences that allow for adaptation and immediate feedback of performance results to raise the Performance Expectancy level of acceptance by students (Ahmad & Ghapar, 2019b). Emphasis on the direct benefits of technology, which range from efficient grading to knowledge retention and efficient collaborative learning, can help reduce existing skepticism among students and faculty members towards technology. In addition, technology-driven dashboards for analytics can serve as a positive incentive for students to achieve their goals with respect to their personal performance related to technology utilization.

5.3.4 Infrastructure and Support

Facilitating Conditions - Technologists' Support from the technologists is paramount for the successful integration of AI to achieve sustainability by encompassing not only technology availability but also the readiness of institutions and human structures for the provision of support. Access to the Internet, a safe storage system, and cloud technology form the basis of an AI-supported educational system; however, this should be complemented by human resource workers skilled in technology to aid students further (AlDhaen, 2022). Furthermore, it would be prudent for management to create a learning pipeline for workers to acquire skills for integration into learning programs. Institutions may provide further innovation labs for AI technology to fulfill the activities of diagnosis and experimentation for the technology. Availability at various levels offers a smooth transition to an AI-supported learning environment for teachers and students.

5.3.5 Cross-Cultural Insights

The relative consistency of the extended UTAUT model for the Indian and UAE contexts means that the best practices for the facilitation of education with AI can be replicated for similar contexts elsewhere. Collaborations between higher educational institutions for similar contexts may expedite the advancement of knowledge dissemination, innovation, and development of similar standards for AI applications in similar contexts. Furthermore, collaborative initiatives may expedite the development of student and faculty exchanges for digital literacy learning programs, including an increased understanding of AI applications in an intercultural context. Furthermore, an open-source project for developing AI-based learning using AI may expedite increased access to AI applications for similar settings elsewhere around the globe.

6 Conclusion and Policy Implications

This study examines the determinants of acceptance, usage behavior, and academic achievements of artificial intelligence (AI)-based academic support systems in the United Arab Emirates (UAE) and Indian institutions of higher learning. The study yielded rich empirical data on the determinants of behavioral intention, actual usage, and student satisfaction in AI-enabled learning settings using an extended Unified Theory of Acceptance and Use of Technology (UTAUT).

The results show that Performance Expectancy, Information Accuracy, and Pedagogical Fit have a significant impact on Behavioral Intention, which means that perceived usefulness, reliability, and alignment with academic requirements can play an important role in influencing the adoption of AI. Moreover, the impact of Behavioral Intention on Actual Use, in turn, leads to increased satisfaction, which proves that a positive attitude towards AI tools is the key to long-term engagement and better learning. The correlation between Satisfaction and Academic Performance is also strong and positive, which makes it even clearer that affective responses are helpful in determining the outcomes of education.

The mediation analysis shows that satisfaction is a significant mediator between AI usage and academic performance, and Behavioral Intention is a mediation variable between the technological aspects and actual usage behavior. Moreover, the cross-country analysis shows that the model is robust in both UAE and India, with some contextual differences indicating that students in India are more concerned with performance efficiency, while students in the UAE are more concerned with information credibility and accuracy.

This study offers a distinct and novel addition to the body of knowledge by diversifying the UTAUT framework with AI-specific elements, that is, information accuracy and pedagogical fit, and simultaneously incorporates behavioral and affective mechanisms in a single analytical framework. In contrast to previous studies on the use of e-learning systems or country-specific situations, the current study provides cross-country empirical confirmation and offers a multidimensional approach to integrating technological, pedagogical, and behavioral aspects of AI-based education.

This study has several limitations that should be mentioned, regardless of its contributions. First, the cross-sectional research design is limiting because causal relationships cannot be declared over time. Moreover, while spurious regression concerns associated with non-stationary time-series data (Cheng et al., 2021, 2022; Wong, Cheng, & Yue, 2024) do not directly apply to this cross-sectional PLS-SEM framework, the possibility of misleading inference even with stationary variables (Wong & Pham, 2022a, 2022b, 2023a, 2023b; Wong & Yue, 2024) cannot be entirely dismissed. Future research employing longitudinal or time-series designs should conduct unit root and cointegration tests prior to model estimation. Second, the sample size is not representative of smaller and less technologically advanced universities in UAE and India, as it includes major universities, which limits its generalizability. Third, the data were collected using self-reported surveys, which can result in common method bias; however, the diagnostic tests indicated that the problem was not critical.

The limitations of this study can be overcome in future studies by implementing longitudinal or experimental research designs to determine the dynamic nature of AI acceptance behavior. Additionally, objective measures, including learning management system (LMS) data or actual academic performance records, would enhance the accuracy of the measurements. More research is also needed to incorporate other variables, such as AI ethics awareness, technology-related anxiety, and institutional trust. It would be interesting to compare the use of AI in different fields (e.g., engineering and social sciences) and countries (e.g., South Asia, the Middle East, and Europe) to better understand the differences in the patterns of AI adoption and increase the external validity of the results.

6.1 Policy and Practical Implications

6.1.1 Institutional Strategy and Governance

More extensive AI integration strategies should be used to match institutional goals with national innovation policies, such as India's National Education Policy 2020 and the UAE Vision 2031 (UNESCO, 2023). Ethical AI usage, transparency, and responsible data management practices should also be established within institutions through well-structured governance frameworks. Simultaneously, policies for responsible use in terms of data governance are required (OECD, 2022).

6.1.2 Curriculum Design and Pedagogical Integration

Considering the importance of Pedagogical Fit, AI tools should be integrated into curriculum design rather than being considered an additional resource. Curriculum development that considers educators and instructional designers is obligatory (Alyoussef, 2021). The introduction of AI literacy and adaptive learning systems can also be used to augment personalized learning and critical interaction with AI-generated content.

6.1.3 Infrastructure and Capacity Building

Long-term investment in technological infrastructure, such as high-speed Internet, secure cloud services, and AI-compatible platforms, is required to facilitate adoption. Training programs related to AI-based practices in teaching must be institutionalized (AlDhaen, 2022). Moreover, uninterrupted technical support systems are necessary to guarantee the success of long-term implementation.

6.1.4 Encouraging Engagement and Innovation

Student engagement and innovativeness are essential for continuous AI adoption. Motivation can be increased with the help of AI-enabled tools that involve gamification, collaboration, and interactive learning (Ouyang et al., 2022). Innovation labs and AI research centers can also contribute to developing an experimental culture and constant improvement in educational institutions.

6.1.5 Cross-Border Collaboration

The similarities in the results for the UAE and India point to the high prospect of cross-border academic cooperation in the field of AI-enabled education. Knowledge transfer can occur through joint research projects, student exchange programs, and collaborative AI-based education systems, which can enhance policy harmonization among regions. This type of cooperation will help create standardized guidelines on the quality assurance and ethical compliance of AI, as well as responsible application, ensuring that the implementation of AI in higher education will not be biased, obscure, or less influential across the world.

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