



DOES CULTURE MATTER IN AI ADOPTION? EXTENDING TAM2 WITH POWER DISTANCE IN SAUDI HIGHER EDUCATION

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ABSTRACT

Aim/Purpose	This study investigates factors influencing faculty adoption of AI-powered educational assistants in Saudi higher education, examining how perceptions of technology and cultural hierarchy shape behavioral intention and actual use.
Background	This paper extends a simplified Technology Acceptance Model 2 (TAM2) by integrating power distance as a cultural variable and examining its direct and moderating effects alongside perceived ease of use, perceived usefulness, and output quality.
Methodology	Quantitative survey data were collected from 268 faculty members across twelve public Saudi universities and analyzed using PLS-SEM with 5,000 bootstrapping resamples.
Contribution	This study extends TAM2 by showing that power distance has a significant direct association with behavioral intention but does not significantly moderate the relationships between perceived usefulness, perceived ease of use, and behavioral intention.

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Findings	Power distance was the strongest direct effect on behavioral intention, followed by perceived ease of use and perceived usefulness. Output quality and perceived ease of use also showed significant positive effects on perceived usefulness. Behavioral intention strongly predicted actual use. Power distance had a significant positive direct effect on behavioral intention but did not significantly moderate the relationships between perceived usefulness and behavioral intention or between perceived ease of use and behavioral intention.
Recommendations for Practitioners	Higher education institutions should emphasize the practical value, ease of use, and output quality of AI-powered educational assistants. Implementation strategies should also consider hierarchical cultural contexts when designing institutional AI adoption initiatives.
Recommendations for Researchers	Future research should examine the role of power distance, potentially using multi-group analysis better to capture cultural heterogeneity across faculty groups or institutional types. Additionally, researchers should explore the role of other Hofstede cultural dimensions – such as individualism vs. collectivism, uncertainty avoidance, and long-term orientation – as potential factors influencing AI adoption in diverse educational contexts.
Impact on Society	The findings suggest that successful AI integration in higher education, particularly in hierarchical societies, hinges on demonstrating clear professional value. This can accelerate the modernization of educational systems, improve teaching and learning outcomes, and position institutions for future technological advancements while remaining culturally attuned.
Future Research	Building on this study, research should explore other potential moderators of the intention-behavior link and investigate how additional cultural dimensions (e.g., uncertainty avoidance, collectivism) shape technology acceptance. Applying the model to other cultural contexts or using multi-group analysis to compare faculty across different academic ranks or disciplines would further validate and refine the understanding of cultural influences on AI adoption.
Keywords	AI adoption, higher education, Technology Acceptance Model 2, TAM2, power distance, faculty, Saudi Arabia

INTRODUCTION

Artificial intelligence (AI) has rapidly emerged as one of the most transformative technologies across all sectors, including higher education. Universities around the world are increasingly adopting AI-driven systems to enhance instructional quality, streamline administrative processes, and offer personalized learning experiences (Vashishth et al., 2024). AI-driven educational assistants – tools that can support grading, generate teaching materials, and provide feedback – represent a significant step toward intelligent learning environments. However, despite these promising capabilities, faculty adoption of AI remains inconsistent. In many academic settings, particularly within cultures characterized by hierarchical structures, the integration of AI technologies continues to face resistance or slow uptake (Alalwan et al., 2018; Dwivedi et al., 2021). Understanding the determinants of faculty members' intention to use AI in teaching is therefore critical to realizing the transformative potential of these tools.

The theoretical foundation of this study is the Technology Acceptance Model 2 (TAM2), which extends the original Technology Acceptance Model (TAM) by incorporating social and cognitive determinants of technology acceptance behavior. The original TAM proposes that Perceived Ease of Use

(PEOU) and Perceived Usefulness (PU) are the primary determinants of behavioral intention and actual system use (Davis, 1989). TAM2 further expands this framework by introducing additional determinants, including Subjective Norm (SN), Image (IM), Job Relevance (JR), Output Quality (OQ), and Result Demonstrability (RD) (Venkatesh & Davis, 2000).

However, prior studies suggest that simplified TAM2 frameworks may provide stronger contextual relevance in emerging technology environments where users have limited experience with the system (Marangunić & Granić, 2015). Accordingly, this study adopts a simplified TAM2 model that retains the core constructs of PEOU, PU, Behavioral Intention to Use AI-driven Educational Assistants (BAII), and Actual Use (AU), together with OQ as a key cognitive determinant.

The inclusion of OQ is particularly important in the context of AI-driven educational assistants because faculty members are likely to evaluate these systems based on the accuracy, reliability, and relevance of AI-generated outputs. High-quality outputs can strengthen perceptions of usefulness and encourage adoption, whereas inaccurate or biased outputs may reduce trust and intention to use the technology (Pavleska & Jerman Blažič, 2017). Therefore, OQ is expected to play a significant role in shaping PU within the proposed framework.

In addition to technological factors, this study incorporates Power Distance (PD) as a cultural moderating variable derived from Hofstede's Cultural Dimensions Theory. PD refers to the extent to which individuals accept unequal distributions of power and hierarchical authority within institutions (Hofstede, 2001). This dimension is particularly relevant in the Saudi higher education context, where organizational hierarchy and authority structures strongly influence decision-making processes (Al-Hujran et al., 2015; Alzahrani et al., 2025).

In high-PD environments, faculty members may rely more heavily on institutional directives and leadership expectations when deciding whether to adopt new technologies, rather than solely on their personal evaluations of usefulness or ease of use. PD may moderate the relationships between TAM2 constructs and behavioral intention to adopt AI.

Despite the growing body of research on educational technology adoption, empirical studies examining AI-driven educational assistants in Saudi higher education remain limited. Existing studies have primarily focused on LMS, e-learning platforms, or general information systems (Alalwan et al., 2018; Tarhini et al., 2015). However, AI technologies differ substantially from traditional systems because they operate with greater autonomy, adaptability, and data-driven decision-making, which may influence users' perceptions of control, reliability, and ethical responsibility.

Another limitation in the literature is the limited integration of cultural moderators within TAM in Middle Eastern educational contexts. Although cultural factors are likely to influence technology adoption behavior, empirical evidence examining the moderating role of PD in AI adoption remains scarce (El-Masri & Tarhini, 2017). Accordingly, this study addresses two major research gaps:

1. The limited empirical research on faculty adoption of AI-driven educational assistants in higher education.
2. The lack of integrated technology acceptance models that incorporate cultural moderation effects, particularly PD, in explaining AI adoption behavior.

Based on the proposed framework, this study aims to:

1. Examine the influence of PEOU on PU of AI-driven educational assistants.
2. Evaluate the effect of PU on Behavioral Intention (BAII) to use AI-driven educational assistants.
3. Assess the impact of OQ on PU of AI-driven systems.
4. Analyze the moderating effect of PD on the relationships between key TAM2 constructs (PU and PEOU) and BAII.

Accordingly, the study is guided by the following research question:

How do technological factors (Perceived Ease of Use, Perceived Usefulness, and Output Quality) and cultural hierarchy (Power Distance) interact to influence faculty members' behavioral intention and actual use of AI-driven educational assistants in Saudi higher education?

This work contributes to both theory and practice. Theoretically, it extends TAM2 by proposing a simplified framework tailored to the early-stage adoption of AI technologies in higher education while integrating cultural moderation through PD. The study also contributes to the growing literature on AI adoption in non-Western contexts by examining how hierarchical cultural structures shape technology acceptance behavior.

Recent studies have investigated generative AI adoption in educational environments. For example, Bamasoud et al. (2025) explored psychological and ethical factors affecting AI adoption among students and lecturers in Saudi universities, while Razi-ur-Rahim et al. (2026) examined faculty adoption in Indian higher education. Similarly, Al-Mamary and Alshammari (2026) extended the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating trust, enjoyment, and ethical concerns to explain AI chatbot adoption in Saudi Arabia. However, none of these studies specifically investigates faculty adoption of AI-driven educational assistants using a simplified TAM2 framework with PD as a cultural moderator. Therefore, this study provides context-sensitive insights into how technological perceptions and hierarchical cultural norms jointly shape AI adoption behavior in Saudi higher education.

LITERATURE REVIEW

This literature review establishes the theoretical foundation and contextual grounding for faculty adoption of AI-driven educational assistants in Saudi higher education. It focuses on TAM and TAM2 constructs, the role of OQ, and the moderating influence of PD.

TECHNOLOGY ACCEPTANCE MODEL (TAM) AND TAM2

Bamasoud et al. (2025) extended TAM with Self-Determination Theory and ethical decision-making to examine GenAI adoption among 578 students and 309 lecturers in Southern Saudi Arabia. Their findings revealed that PU, intrinsic motivation, and ethical trust significantly predicted adoption intention, while academic integrity concerns emerged as key mediators. This dual-perspective approach highlights the importance of examining both faculty and student viewpoints, though their study focused on GenAI in general rather than on specific AI-driven educational assistants. This underscores the need for research specifically targeting AI-driven educational tools, which this study addresses by examining faculty adoption of AI-assisted teaching assistants.

Al-Mamary and Alshammari (2026) extended UTAUT by incorporating perceived trust, enjoyment, and ethics to examine AI chatbot adoption in Saudi higher education. Their study of university students found that perceived trust emerged as the strongest predictor of behavioral intention, followed by performance expectancy and effort expectancy. This underscores the critical role of trust in AI adoption within the Saudi cultural context, aligning with this study's inclusion of output quality as a trust-related determinant. However, their focus on students leaves open the question of how faculty, who operate within hierarchical academic structures, form adoption intentions, a gap this study addresses by incorporating PD as a cultural variable.

In the Indian higher education context, Razi-ur-Rahim et al. (2026) examined faculty adoption of GenAI among 455 educators, finding that PU, PEOU, and OQ primarily drove adoption, while social influence played a minimal role. Their validation of TAM in a non-Western, resource-constrained environment supports this study's simplified TAM2 approach and reinforces the importance of OQ as a key determinant of PU. Their Indian context provides a useful comparison point for examining

how cultural hierarchy may function differently in Saudi Arabia, where PD may exert distinct influences on adoption behavior.

These studies underscore the importance of PU, OQ, and PD in AI adoption across non-Western higher education settings, while revealing the need for faculty-focused research on specific AI-driven educational tools. Building on these recent contextual insights, the theoretical foundations of technology acceptance provide the core framework for this study. Granić and Marangunić (2019) demonstrated that TAM is a robust predictive model across various technologies and contexts.

Venkatesh and Davis (2000) extended TAM to TAM2 (see Table 1 for a comparison of TAM, TAM2, and UTAUT). Table 1 compares TAM, TAM2, and UTAUT across key dimensions, justifying the selection of a simplified TAM2 framework for this study.

Table 1. Comparison of TAM, TAM2, and UTAUT

Feature	TAM (Davis, 1989)	TAM2 (Venkatesh & Davis, 2000)	UTAUT (Venkatesh et al., 2003)
Core constructs	PU, PEOU	PU, PEOU, SN, IM, JR, OQ, RD	PE, EE, SI, FC
Social influence	Not included	Subjective norm, image	Social influence
Cognitive determinants	Not included	Job relevance, output quality, result demonstrability	Not included
Moderators	Not included	Experience, voluntariness	Age, gender, experience, voluntariness
Parsimony	High	Medium	Low
Best suited for	Early-stage, simple systems	Organizational contexts	Complex, multi-user systems
Justification for this study's selection	Not sufficient alone for AI	Most relevant (OQ critical for AI trust)	Too complex for early AI adoption

Beyond TAM-based models, Rogers' (2003) Diffusion of Innovations Theory offers complementary insights into AI adoption in higher education. Rogers conceptualizes adoption as a multi-stage process influenced by innovation attributes: relative advantage (comparable to PU), compatibility (alignment with existing values and practices), and complexity (similar to perceived ease of use). Importantly, Rogers distinguishes between organizational adoption (institutional decisions to acquire or mandate technology) and individual acceptance (faculty members' voluntary use). In hierarchical academic contexts, this distinction is critical: institutional directives may compel compliance without generating genuine acceptance. The present study focuses on individual faculty acceptance, measuring behavioral intention and self-reported actual use, while acknowledging that institutional power structures may influence both adoption and acceptance differently.

As shown in Table 1, while UTAUT offers greater comprehensiveness, its complexity is less suited to early-stage AI adoption, where few moderators have established effects. TAM2 strikes a balance between parsimony and explanatory power, particularly through its inclusion of OQ, a construct critical for AI systems in which trust and reliability are paramount (Pavleska & Jerman Blažič, 2017). In the Saudi AI context, however, JR and RD are difficult to assess without experience, while SN and IM overlap conceptually with PD. A simplified TAM2 retaining PEOU, PU, BAI, AU, and OQ is therefore more appropriate.

Davis (1989) and Venkatesh and Davis (2000) suggest that systems perceived as easier to use are more likely to be considered useful. Therefore:

H1: PEOU positively influences PU.

BEHAVIORAL ADOPTION INTENTION (BAII)

Cortez et al. (2024) and Wang et al. (2025) emphasize that BAII represents faculty motivation and willingness to adopt or continue using AI-driven technology. Behavioral intention is a key predictor of actual engagement with a system, bridging the gap between perception and behavior (Davis, 1989). Research consistently shows that faculty are more likely to adopt AI-driven assistants when they perceive the systems as useful and easy to use, reflecting the fundamental mechanisms of TAM (Venkatesh & Davis, 2000). Almaiah et al. (2020) further confirm that PU is one of the strongest determinants of behavioral intention, particularly in educational contexts where technology directly supports task performance and teaching efficiency. In addition, studies in higher education indicate that faculty intention is not only influenced by PU but is also reinforced by the reliability and quality of outputs generated by the system (Dwivedi et al., 2021; Pavleska & Jerman Blažič, 2017). These findings provide strong theoretical justification for positing that PU directly enhances BAII in the adoption of AI-driven teaching assistants.

Recent generative AI literature has expanded the understanding of adoption factors beyond traditional TAM constructs. Kasneci et al. (2023) provide a comprehensive analysis of large language models in education, identifying both opportunities (content creation, personalized learning, student engagement) and challenges (bias, fact-checking requirements, continuous human oversight). Their work underscores that faculty adoption requires developing new competencies to understand AI limitations, a finding that complements the present study's emphasis on OQ. Similarly, Bearman et al. (2024) examine how generative AI necessitates "evaluative judgement", the capability to judge the quality of AI outputs, and argue that uniquely human capabilities (identifying and calibrating quality) become more critical as AI adoption accelerates. This perspective reinforces why OQ significantly influences PU in the present study's model. Crompton and Burke (2024) offer a systematic collection of AI applications across higher education, including case studies on generative AI, adaptive learning, intelligent tutoring systems, and ethical considerations. These studies highlight that AI adoption research must move beyond general technology acceptance frameworks to address AI-specific factors such as OQ evaluation, ethical oversight, and pedagogical integration, precisely the gaps this study addresses through its simplified TAM2 with PD moderation.

H2: PU positively influences BAII.

Moreover, PEOU can also directly influence BAII by reducing the cognitive effort required to interact with AI systems (Venkatesh & Davis, 2000). When faculty perceive AI assistants as intuitive and easy to use, their willingness to adopt or continue using the system is enhanced, complementing the effect of PU.

H3: PEOU positively influences BAII.

ACTUAL USE (AU)

Venkatesh and Davis (2000) emphasize that AU reflects actual engagement with AI-driven systems, encompassing frequency, duration, and task coverage, whereas self-reported measures of AU are considered valid in educational research because they closely align with actual usage behavior. Al-Mamary (2025), Syed et al. (2025), and Tran and Nguyen (2024) note that faculty intention plays a crucial role in technology adoption. Chanda et al. (2025) and Emon et al. (2023) also indicate that BAII is the most direct predictor of AU, as faculty with a strong intention to use AI-driven assistants are more likely to translate that intention into consistent and sustained engagement. Accordingly, this study hypothesizes that BAII positively influences AU, capturing the connection between faculty motivation and actual interaction with AI-driven educational assistants. Based on prior research and theoretical foundations, it is hypothesized that:

H4: BAII positively predicts AU.

OUTPUT QUALITY (OQ)

Venkatesh and Davis (2000) conceptualize OQ as the user's perception of the accuracy, reliability, and relevance of system outputs. In the context of AI-driven educational assistants, the quality of outputs is critical, as faculty are unlikely to perceive a system as useful if it generates errors, irrelevant feedback, or unreliable information (Eisenberg et al., 2014; Pavleska & Jerman Blažič, 2017). Empirical research further supports the direct impact of OQ on PU, indicating that higher OQ enhances PU and increases the likelihood of adoption (Dwivedi et al., 2021). Faculty rely on AI-generated outputs for grading, content creation, and feedback; therefore, accuracy, consistency, and alignment with teaching objectives are essential prerequisites for perceiving the system as beneficial. High-quality outputs not only improve task efficiency but also build trust, confidence, and acceptance among users, reinforcing the theoretical rationale for including OQ in the model (Venkatesh & Bala, 2008). Based on this reasoning, H5 is proposed:

H5: OQ positively influences PU.

POWER DISTANCE (PD) AS A CULTURAL MODERATOR

Hofstede (2001) defines PD as the extent to which members of an organization accept and expect unequal power distribution. In high-PD cultures, hierarchical authority is normalized, and decision-making is often centralized. Empirical evidence suggests that Saudi Arabia exhibits high PD, characterized by strong top-down directives, hierarchical norms, and reliance on institutional authority (Al-Hujran et al., 2015). In such contexts, faculty may adopt technologies not solely based on personal evaluation of system characteristics, such as PEOU or PU, but also due to compliance with institutional mandates or authoritative encouragement (Alzahrani et al., 2025).

Cultural variables, such as PD, can influence technology adoption in two ways. First, PD may directly influence behavioral intention, as individuals in high-power-distance contexts rely more on institutional authority and hierarchical decision-making when adopting new technologies (Daniels & Greguras, 2014; Khatri, 2009; Li & Rasiah, 2025). Second, PD may function as a moderator, influencing the strength of relationships between TAM constructs and behavioral intention. For instance, in hierarchical settings, the positive impact of PU on BAII may be weakened because faculty rely more on authority guidance than on their individual assessment of usefulness (El-Masri & Tarhini, 2017). Similarly, PEOU may have a diminished effect on BAII in high-PD contexts, as personal convenience is less salient when adoption is influenced by hierarchical norms (Alabri et al., 2020). Based on this theoretical and empirical rationale, the study examines both the direct and moderating roles of PD and proposes the following hypotheses:

H6: PD moderates the relationship between PU and BAII.

H7: PD moderates the relationship between PEOU and BAII.

(Note: The direct effect of PD on BAII is represented in the structural model as a path, though not formalized as a separate hypothesis.)

ETHICAL CONCERNS IN AI ADOPTION

Faculty adoption of AI-driven educational assistants raises distinct ethical concerns that TAM2 does not directly address. Unlike conventional information systems, AI tools operate with varying degrees of autonomy, algorithm opacity, and potential bias (Kasneci et al., 2023). Faculty may hesitate to adopt AI assistants due to concerns about: (a) data privacy and student information security; (b) algorithmic bias in grading or feedback generation; (c) loss of pedagogical autonomy when AI makes instructional recommendations; and (d) transparency and explainability of AI decisions (Bearman et al., 2024). While the present study captures OQ as a trust-related determinant, future research should explicitly model ethical concerns as antecedents or moderators of PU and behavioral intention.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

This study employs Structural Equation Modeling (SEM), as illustrated in Figure 1, to examine the factors influencing faculty BAI toward AI-driven teaching assistants. The model integrates constructs from the TAM and its extension TAM2, complemented by cultural considerations, to provide a comprehensive understanding of faculty adoption behavior in Saudi higher education.

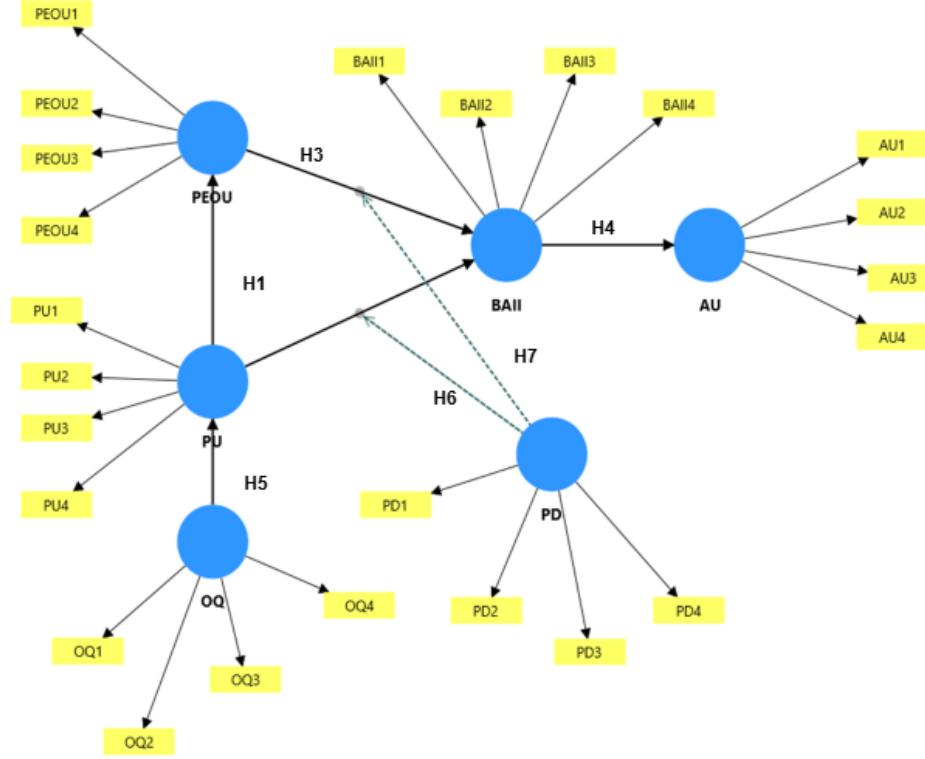


Figure 1. Conceptual research model

The core TAM constructs, PEOU and PU, form the foundation of the conceptual research model. PEOU reflects the extent to which faculty perceive AI systems as intuitive, clear, and effortless to use. Higher PEOU reduces cognitive effort, builds confidence, and facilitates adoption. PU measures faculty perceptions of how AI assistants enhance productivity, improve teaching effectiveness, and support overall task performance.

According to TAM, systems perceived as both easy to use and useful are more likely to positively influence BAI (Davis, 1989; Venkatesh & Davis, 2000). BAI captures faculty motivation and intention to adopt or continue using AI-driven teaching assistants. As the most direct predictor of AU, BAI bridges the gap between perception and behavior, enabling the study to evaluate faculty readiness to integrate AI into teaching practices and predict actual engagement. Complementing this, AU reflects real system use, including frequency, duration, and scope of interaction. AU1–AU4 adequately measure usage without requiring separate system-recorded items, as self-reported interaction aligns with the study's objectives and established TAM conventions (Venkatesh & Davis, 2000).

The model incorporates OQ as an extension of TAM2. OQ reflects the accuracy, reliability, and relevance of AI-generated outputs. High-quality outputs enhance PU and, in turn, increase BAI, ensuring that faculty value both the system's functionality and the results it produces.

Alabri et al. (2020) highlight the importance of contextual influences in technology adoption; accordingly, PD is included as a moderating variable. Derived from Hofstede's framework, PD measures

the degree to which individuals accept hierarchical authority and unequal power distribution (Hofstede, 2001; Yoo et al., 2011). In high PD contexts, faculty may rely more on institutional norms or guidance from authority than on personal evaluation of system characteristics, potentially weakening the effects of PEOU and PU on BAI. Including PD allows the model to capture culturally contingent adoption patterns and strengthens the explanatory power of TAM2 constructs in Saudi higher education.

These constructs form a robust conceptual research model for understanding AI adoption. PEOU and PU explain faculty perceptions. BAI captures intention, AU reflects actual engagement, OQ ensures output effectiveness is considered, and PD accounts for cultural moderation. This integrated model balances parsimony with explanatory richness, providing a comprehensive approach for examining the behavioral and contextual drivers of BAI toward AI-driven teaching assistants, as illustrated in Figure 1.

RESEARCH METHODOLOGY

Quantitative approaches are particularly well-suited to testing theoretically grounded models, such as the TAM and its extensions (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). By extending TAM2 with OQ and PD moderation, the design captures both technological perceptions and cultural dynamics influencing faculty adoption behavior. The use of validated instruments, a purposively selected sample, and robust statistical analysis provides a suitable basis for examining technology adoption theory and practical AI integration strategies within higher education contexts.

RESEARCH DESIGN

The selection of TAM2 as the theoretical foundation is justified because it extends the core TAM by incorporating cognitive and social determinants such as OQ, while maintaining parsimony and predictive validity (Venkatesh & Davis, 2000). Moreover, previous research in educational technology has successfully used simplified TAM2 frameworks to examine technology adoption among educators (Amouri et al., 2025; Marian et al., 2025). Hence, this model offers a balance between theoretical rigor and contextual adaptability to Saudi higher education, where hierarchical norms and emerging AI integration coexist.

POPULATION AND SAMPLING

The study targeted faculty members from the top twelve public Saudi universities, as identified in the 2024–2025 Shanghai Academic Ranking of World Universities (ARWU) among the world's top 1000 institutions (Shanghai Ranking, 2025). These twelve universities, listed in Table 2 from highest (King Saud University) to lowest (Jazan University) ranking, represent leading public higher education institutions across the Kingdom and were purposefully selected to capture perspectives from academically competitive and research-active environments. The focus was on universities housing Colleges of Business, Business Administration, Computer Science, and Engineering, as these disciplines are most actively engaged in digital transformation and the integration of AI-assisted pedagogical tools.

A total of 350 faculty members were invited through institutional mailing lists and professional academic networks. After screening for completeness and data quality, 268 valid responses were retained, yielding a response rate of approximately 76.6%. The sample represented a well-qualified academic cohort, comprising BSc (14.9%), Master's (32.8%), and PhD (52.2%) holders. The age distribution was predominantly in the 25–34 years (35.5%) and 35–44 years (29.8%) age groups, followed by 45–54 years (22.4%) and 55 years or older (12.3%). Female participants accounted for 64.2%, while males represented 35.8% of the sample. Respondents' experience with AI technologies ranged from less than one year (33.6%) to more than six years (10.4%), with 14.9% reporting no prior experience. This purposively selected sample provides a suitable basis for analyzing faculty perceptions, behavioral intentions, and actual use of AI-driven educational tools through structural equation modeling. The demographic characteristics of the respondents are summarized in Table 2.

A purposive sampling approach was used to target faculty members in relevant disciplines. This approach ensured representation across different academic disciplines, genders, and institutional contexts, thereby enhancing the diversity and relevance of the sample (Creswell, 2012).

Table 2. Participant demographics overview

Demographic variable	Category	Frequency	Valid percent (%)	Cumulative percent (%)
Degree	BSc	40	14.93	14.93
	Master	88	32.84	47.77
	PhD	140	52.24	100.00
Age Group	25–34	95	35.45	35.45
	35–44	80	29.85	65.30
	45–54	60	22.39	87.69
	55+	33	12.31	100.00
Sex	Female	172	64.18	64.18
	Male	96	35.82	100.00
Institute Name: 1	King Saud University (~90)	25	9.33	9.33
2	King Abdulaziz University (201–300)	24	8.96	18.29
3	King Abdullah University of Science and Technology (201–300)	15	5.60	23.89
4	Princess Nourah bint Abdulrahman University (301–400)	18	6.72	30.61
5	King Khalid University (401–500)	20	7.46	38.07
6	Taif University (401–500)	18	6.72	44.79
7	Prince Sattam bin Abdulaziz University (601–700)	22	8.21	53.00
8	King Fahd University of Petroleum & Minerals (701–800)	21	7.84	60.84
9	Qassim University (701–800)	15	5.60	66.44
10	Umm Al-Qura University (701–800)	28	10.45	76.89
11	King Faisal University (801–900)	25	9.33	86.22
12	Jazan University (901–1000)	37	13.81	100.00
Experience in AI	Less than 1 year	90	33.58	33.58
	1–3 years (AI Users Only)	80	29.85	63.43
	4–6 years	30	11.19	74.63
	More than 6 years	28	10.45	85.07
	Never used AI	40	14.93	100.00

Note: “Less than 1 year” refers only to respondents with prior AI use; “Never used AI” is reported as a separate category.

A power analysis using G*Power 3.1 indicated that a minimum of 200 participants would be sufficient to detect a medium effect size ($f^2 = 0.15$) with 80% power and a 0.05 significance level. The

achieved sample size of 268, therefore, exceeds the minimum recommended threshold for Structural Equation Modeling (SEM) and provides a robust basis for hypothesis testing (Hair & Alamer, 2022; Hair et al., 2022).

A limitation of purposive sampling is that the findings may not generalize to faculty at non-ranked universities, private institutions, or to disciplines outside business, computer science, and engineering. Readers should exercise caution when applying these results to dissimilar contexts.

INSTRUMENT DEVELOPMENT

The survey instrument consisted of six constructs aligned with the proposed model: PEOU, PU, OQ, BAI, AU, and PD. All items were adapted from validated scales in prior literature to ensure content validity. A few items were slightly modified or newly created to reflect the specific context of AI-driven educational assistants in Saudi higher education. Each item was measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The operationalization of constructs is summarized below:

- PEOU: Adapted from Davis (1989), comprising four items (PEOU1–PEOU4) assessing the degree to which AI tools are perceived as user-friendly and effortless to operate.
- PU: Derived from Davis (1989) and Venkatesh and Davis (2000), including four items (PU1–PU4) evaluating how AI-driven systems enhance teaching effectiveness and efficiency.
- OQ: Based on Venkatesh and Bala (2008), with four items (OQ1–OQ4) capturing perceptions of the accuracy, reliability, and relevance of AI-generated outputs.
- BAI: Adapted from Venkatesh et al. (2003) and Cortez et al. (2024), consisting of four items (BAI1–BAI4) assessing faculty willingness and motivation to adopt AI systems.
- AU: Derived from Emon et al. (2023), measured through four self-reported items (AU1–AU4) reflecting the frequency and extent of AI tool usage in teaching. Self-reported AU measures are widely accepted in technology acceptance research, with meta-analyses confirming strong correlations with objective usage ($r = 0.71\text{--}0.85$) (Turner et al., 2010; Venkatesh & Davis, 2000). System logging was unavailable across all twelve universities, so AU items focused on specific, verifiable behaviors (frequency, task coverage, and workflow integration). The strong BAI→ AU association is consistent with the expected intention-behavior relationship.
- PD: Measured using Hofstede's (2001) scale, modified for educational contexts, with four items (PD1–PD4) evaluating acceptance of hierarchical authority and institutional influence on technology decisions.

The instrument was pilot-tested with 30 faculty members to assess item clarity, internal consistency, and cultural relevance within the Saudi higher education context. Feedback from participants led to minor linguistic refinements, ensuring that the terminology and phrasing were contextually appropriate and easily understood. The complete survey instrument and measurement items are presented in the Appendix.

As presented in Table 3, Cronbach's alpha values ranged from 0.697 to 0.750, meeting or closely approaching the minimum threshold of 0.70 recommended for exploratory and early-stage research (Hair & Alamer, 2022).

DATA COLLECTION PROCEDURES

Data were collected using an online questionnaire administered via Google Forms from May 21, 2025, to July 25, 2025. The survey link was distributed electronically to faculty members at 12 Saudi higher education institutions, as listed in Table 2. All participants were 25 years of age or older and held a BSc, Master's, or PhD degree.

Formal written consent was unnecessary because of the study's anonymous design. Participation was completely voluntary, and consent was considered given when respondents completed the questionnaire after being informed at the start of the survey that their responses would be kept anonymous and confidential. Respondents confirmed their willingness to participate by selecting an "I Agree to Participate" option before accessing the questionnaire, ensuring that consent was obtained voluntarily and before data collection. No identifying or sensitive information was requested, and all data were collected solely for research purposes, protecting participant privacy and minimizing social desirability bias.

DATA ANALYSIS APPROACH

Data were analyzed using SmartPLS 4, enabling assessment of both the measurement and structural models through Partial Least Squares Structural Equation Modeling (PLS-SEM) (Cheah et al., 2024). PD was included in the structural model both as a direct predictor of BAI and as a moderator of the relationships between PU, PEOU, and BAI.

The analysis proceeded in three stages:

1. **Measurement model assessment:** evaluation of indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity using the AVE, and discriminant validity using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT).
2. **Structural model assessment:** examination of multicollinearity using the Variance Inflation Factor (VIF), followed by evaluation of path coefficients, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and moderation effects ($PD \times PEOU$ and $PD \times PU \rightarrow BAI$).
3. **Bootstrapping procedure:** A bootstrapping procedure with 5,000 resamples was applied to test the statistical significance of all structural paths. Significance was evaluated using t-values and p-values derived from the bootstrapping results.

COMMON METHOD BIAS AND GENDER INVARIANCE

Because all data were self-reported, common method bias was assessed using Harman's single-factor test. An unrotated principal component analysis extracted six factors with eigenvalues >1.0 ; the first factor accounted for 28.4% of total variance, below the 50% threshold, indicating that common method bias is unlikely to distort findings (Podsakoff et al., 2003).

Regarding gender distribution (64.2% female, 35.8% male), this reflects the actual faculty composition in Saudi public universities according to the Ministry of Education (2024) data, not differential response bias. Multi-group analysis (MGA) comparing male and female faculty revealed no statistically significant differences in any path coefficient (all $p > 0.05$), suggesting that the model operates similarly across genders.

ETHICAL CONSIDERATIONS

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Ethical approval was obtained from the Local Committee for Research Ethics at Jazan University (IRB Registration No.: HAPO-10-Z-001; Approval Reference No.: REC-46/11/1537; Approved on May 15, 2025).

Because the study used an anonymous online questionnaire and involved no medical or invasive procedures, the ethics committee waived formal written consent. Instead, implied informed consent was obtained electronically. Before accessing the survey, participants were provided with an information sheet explaining the study purpose, voluntary participation, confidentiality, and the right to withdraw at any time without penalty. Participants then selected an "I Agree to Participate" option before completing the questionnaire.

All responses were collected anonymously, and no personally identifying information was recorded. Data were stored securely on a password-protected university server accessible only to the research team. Participants could withdraw at any time before survey submission; however, withdrawal after submission was not possible due to the anonymous design. No incentives were provided for participation. The study posed minimal risk to participants, limited mainly to minor fatigue associated with completing the questionnaire. No sensitive personal information was collected.

RESULTS/DATA ANALYSIS

This section reports the findings from the PLS-SEM analysis in three stages. First, the measurement model is assessed for reliability, convergent validity, and discriminant validity. Second, the structural model is evaluated to test the seven hypotheses, including direct and moderating effects. Third, the model's explanatory and predictive power is examined using R^2 , f^2 , and Q^2 statistics. Before turning to the detailed statistics, three principal findings warrant emphasis. First, PD had the strongest direct effect on BAI, followed by PEOU and PU. Second, PD had a significant direct effect on BAI but did not moderate the relationships between PU, PEOU, and BAI, a finding that refines theoretical assumptions about how PD operates in technology acceptance. Third, the model explains 70.6% of the variance in AU and 63.5% of the variance in BAI, indicating substantial explanatory power.

MEASUREMENT MODEL ASSESSMENT

The measurement model was assessed in SmartPLS 4 to evaluate construct reliability and validity (Ghaleb et al., 2021; Ringle et al., 2024). Convergent validity was assessed using AVE and CR. As shown in Table 3, all constructs demonstrated AVE values greater than 0.50 and CR values exceeding 0.70, indicating that each construct adequately captures the variance of its indicators (Hair & Alamer, 2022).

These values indicate that each construct explains more than half of the variance in its indicators, supporting convergent validity. Internal consistency reliability was assessed using Cronbach's alpha and CR, both of which exceeded the recommended threshold of 0.70 for most constructs except OQ ($\alpha=0.697$). For a visual representation of the construct loadings and the relationships among the latent variables, see Figure 2, which displays the results of the PLS Algorithm estimation.

Table 3. Construct reliability and convergent validity

Construct	Cronbach's alpha	CR	AVE	Interpretation
AU	0.738	0.833	0.556	Reliable & valid
BAI	0.718	0.825	0.542	Reliable & valid
OQ	0.697	0.815	0.525	Acceptable for early-stage/exploratory research
PD	0.704	0.818	0.530	Reliable & valid
PEOU	0.750	0.842	0.571	Reliable & valid
PU	0.725	0.828	0.547	Reliable & valid

The indicator loadings were examined using the PLS algorithm. Most indicators showed satisfactory loadings, although AU4 and OQ4 were slightly below the commonly recommended threshold of 0.70. These indicators were retained because the construct-level reliability and AVE values remained within acceptable ranges, and the items were theoretically relevant to their respective constructs. The individual outer loadings are reported in Table 4.

The OQ construct recorded a Cronbach's alpha of 0.697, marginally below the conventional 0.70 threshold. Deleting any individual OQ item produced only a marginal change in Cronbach's alpha and did not improve it sufficiently to justify item removal. The CR of 0.815 supports internal consistency, while the AVE of 0.525 supports convergent validity. (Fornell & Larcker, 1981). Given the

theoretical importance of OQ in AI adoption and the contextualized nature of this research, the OQ construct was retained as originally specified. Future studies may consider refining or expanding the OQ items to improve internal consistency.

Table 4. Outer loadings

Construct	Indicator	Outer loading
Actual Use	AU1	0.803
	AU2	0.738
	AU3	0.746
	AU4	0.693
Behavioral Intention to Use AI	BAII1	0.798
	BAII2	0.708
	BAII3	0.727
	BAII4	0.709
Output Quality	OQ1	0.726
	OQ2	0.728
	OQ3	0.761
	OQ4	0.680
Power Distance	PD1	0.706
	PD2	0.743
	PD3	0.705
	PD4	0.755
Perceived Ease of Use	PEOU1	0.705
	PEOU2	0.766
	PEOU3	0.782
	PEOU4	0.768
Perceived Usefulness	PU1	0.726
	PU2	0.751
	PU3	0.749
	PU4	0.732

Discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratio (Cheung et al., 2024; Dirgiamto, 2023). The Fornell–Larcker results in Table 5 indicate potential concerns regarding discriminant validity, as several inter-construct correlations exceed the corresponding square roots of the AVEs. Therefore, the Fornell–Larcker criterion alone does not provide consistent evidence of discriminant validity. The HTMT results in Table 6 provide additional evidence, although some values are close to or exceed the conservative 0.85 threshold. The results provide partial evidence of discriminant validity, and the distinctiveness of some constructs should be interpreted with caution. Table 6 presents the HTMT ratios along with their 95% bootstrapped confidence intervals.

Table 5. Fornell–Larcker criterion

	AU	BAIL	OQ	PD	PEOU	PU
AU	0.746					
BAIL	0.840	0.736				
OQ	0.777	0.761	0.724			
PD	0.788	0.736	0.793	0.728		
PEOU	0.782	0.710	0.705	0.712	0.756	
PU	0.775	0.704	0.723	0.744	0.696	0.740

Table 6. Heterotrait–Monotrait Ratio (HTMT) with 95% confidence intervals

Relationship	Original sample (O)	Sample mean (M)	2.5% CI	97.5% CI
BAIL ↔ AU	0.812	0.815	0.742	0.873
OQ ↔ AU	0.795	0.798	0.724	0.859
OQ ↔ BAIL	0.834	0.837	0.768	0.898
PD ↔ AU	0.871	0.874	0.803	0.924
PD ↔ BAIL	0.742	0.747	0.681	0.805
PD ↔ OQ	0.864	0.867	0.791	0.918
PEOU ↔ AU	0.810	0.812	0.739	0.875
PEOU ↔ BAIL	0.689	0.692	0.621	0.749
PEOU ↔ OQ	0.756	0.759	0.688	0.826
PEOU ↔ PD	0.704	0.707	0.642	0.773
PU ↔ AU	0.845	0.848	0.774	0.909
PU ↔ BAIL	0.792	0.796	0.721	0.862
PU ↔ OQ	0.711	0.714	0.639	0.774
PU ↔ PD	0.826	0.829	0.758	0.887
PU ↔ PEOU	0.765	0.769	0.693	0.832

The HTMT values ranged from 0.689 to 0.871. Most ratios were below 0.85, although the PD–AU and PD–OQ relationships exceeded this conservative threshold (Hair et al., 2020). However, their confidence intervals did not include 1.00. The HTMT results therefore provide partial evidence of construct distinctiveness, although some relationships require cautious interpretation (Henseler et al., 2015). For a visual representation of the construct loadings and the relationships among the latent variables, Figure 2 displays the results of the PLS algorithm estimation. Although Figure 2 includes path coefficients for completeness, the focus of the measurement model assessment is on the factor loadings (shown as arrows from constructs to indicators).

STRUCTURAL MODEL ASSESSMENT

The structural model was evaluated using PLS-SEM with 5,000 bootstrap resamples. Table 7 reports the path coefficients, sample means, standard deviations, t-values, p-values, effect sizes (f^2), and VIF values for the direct and moderating effects.

Direct effects (H1–H5): The hypothesized direct relationships were statistically significant. BAIL had a strong positive effect on AU ($\beta = 0.840$, $p < 0.001$), indicating that behavioral intention is strongly associated with actual use. $OQ \rightarrow PU$ ($\beta = 0.723$, $p < 0.001$) and $PEOU \rightarrow PU$ ($\beta = 0.696$, $p < 0.001$) were also positive and significant, indicating that OQ and PEOU are associated with higher PU. The direct effects of PD ($\beta = 0.348$, $p < 0.001$), PEOU ($\beta = 0.296$, $p < 0.001$), and PU ($\beta = 0.244$, $p < 0.001$) on BAIL were likewise positive and significant.

The significant positive effect of PD on BAII indicates that PD is positively associated with behavioral intention to adopt AI. However, the moderation results indicate that PD does not significantly change the effects of PEOU or PU on BAII.

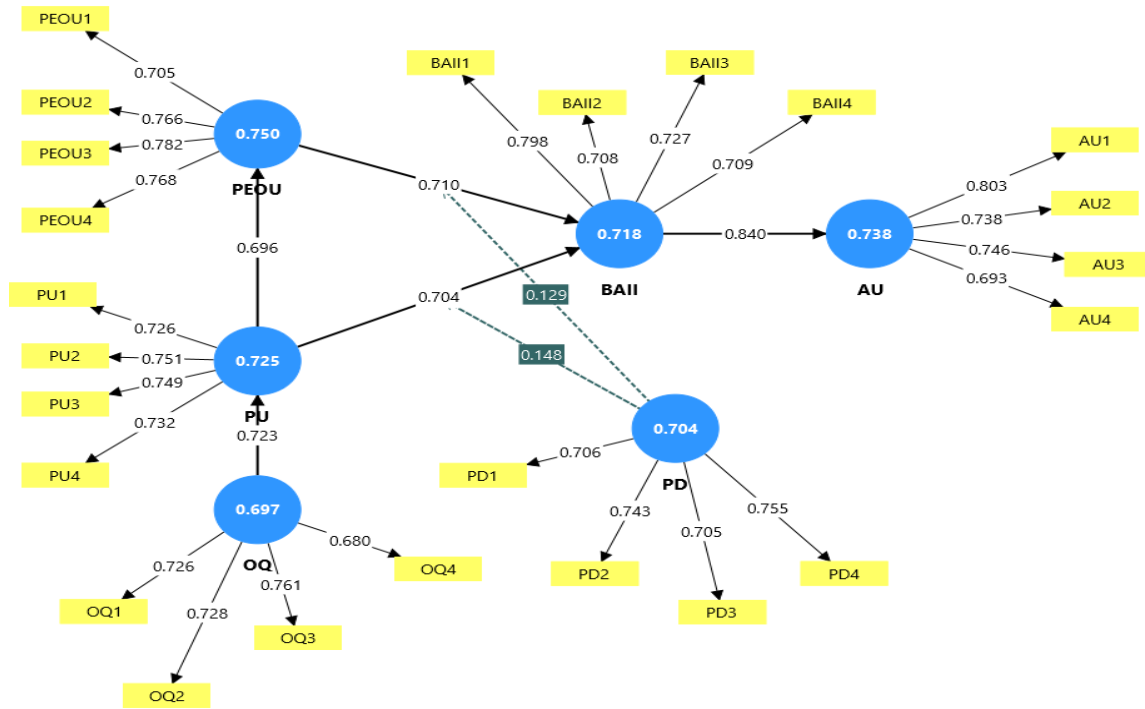


Figure 2. Measurement model assessment

Moderating effects (H6–H7): The moderating effects were not statistically significant. The interaction between PD and PEOU was not significant ($\beta = 0.003$, $p = 0.952$), and the interaction between PD and PU was also not significant ($\beta = -0.014$, $p = 0.787$), as shown in Table 7. Therefore, H6 and H7 were not supported. These findings indicate that PD does not significantly alter the relationships between PEOU and BAII or between PU and BAII. Both interaction effects also had negligible effect sizes ($f^2 = 0.000$).

Following Cohen's (1988) guidelines, $\text{BAII} \rightarrow \text{AU}$ ($f^2 = 2.397$) and $\text{PEOU} \rightarrow \text{PU}$ ($f^2 = 0.939$) had large effect sizes. $\text{OQ} \rightarrow \text{PU}$ ($f^2 = 0.296$) had a medium effect size, whereas $\text{PD} \rightarrow \text{BAII}$ ($f^2 = 0.123$), $\text{PEOU} \rightarrow \text{BAII}$ ($f^2 = 0.103$), and $\text{PU} \rightarrow \text{BAII}$ ($f^2 = 0.063$) had small effect sizes. The VIF values ranged from 1.000 to 1.510, remaining below the recommended threshold of 3.0, indicating that multicollinearity was not a concern (López-Costa et al., 2025).

Table 7. Structural model results

Construct/path	β (Path coefficient)	Sample mean (M)	STDEV	t-value	p-value	f^2	VIF range
Direct effects							
$\text{BAII} \rightarrow \text{AU}$	0.840	0.842	0.015	54.917	<0.001	2.397	1.319 – 1.464
$\text{OQ} \rightarrow \text{PU}$	0.723	0.725	0.038	19.074	<0.001	0.296	1.317 – 1.463

Construct/path	β (Path coefficient)	Sample mean (M)	STDEV	t-value	p-value	f^2	VIF range
PD $\rightarrow$ BAII	0.348	0.351	0.067	5.211	<0.001	0.123	1.220 – 1.409
PEOU $\rightarrow$ BAII	0.296	0.293	0.061	4.836	<0.001	0.103	1.338 – 1.398
PU $\rightarrow$ BAII	0.244	0.246	0.062	3.912	<0.001	0.063	1.000
PEOU $\rightarrow$ PU	0.696	0.697	0.039	17.692	<0.001	0.939	1.000
Moderating effects							
PD $\times$ PEOU $\rightarrow$ BAII	0.003	0.005	0.056	0.060	0.952	0.000	1.259 – 1.433
PD $\times$ PU $\rightarrow$ BAII	-0.014	-0.013	0.052	0.270	0.787	0.000	1.313 – 1.510

Figure 3 provides a visual summary of the structural model, highlighting the magnitude and significance of the path coefficients. As illustrated in Figure 3 and reported in Table 7, BAII is the strongest predictor of AU ($\beta = 0.840$), and OQ strongly influences PU ($\beta = 0.723$). Figure 3 also depicts the nonsignificant moderating effects of PD, represented by the dashed paths from the interaction terms.

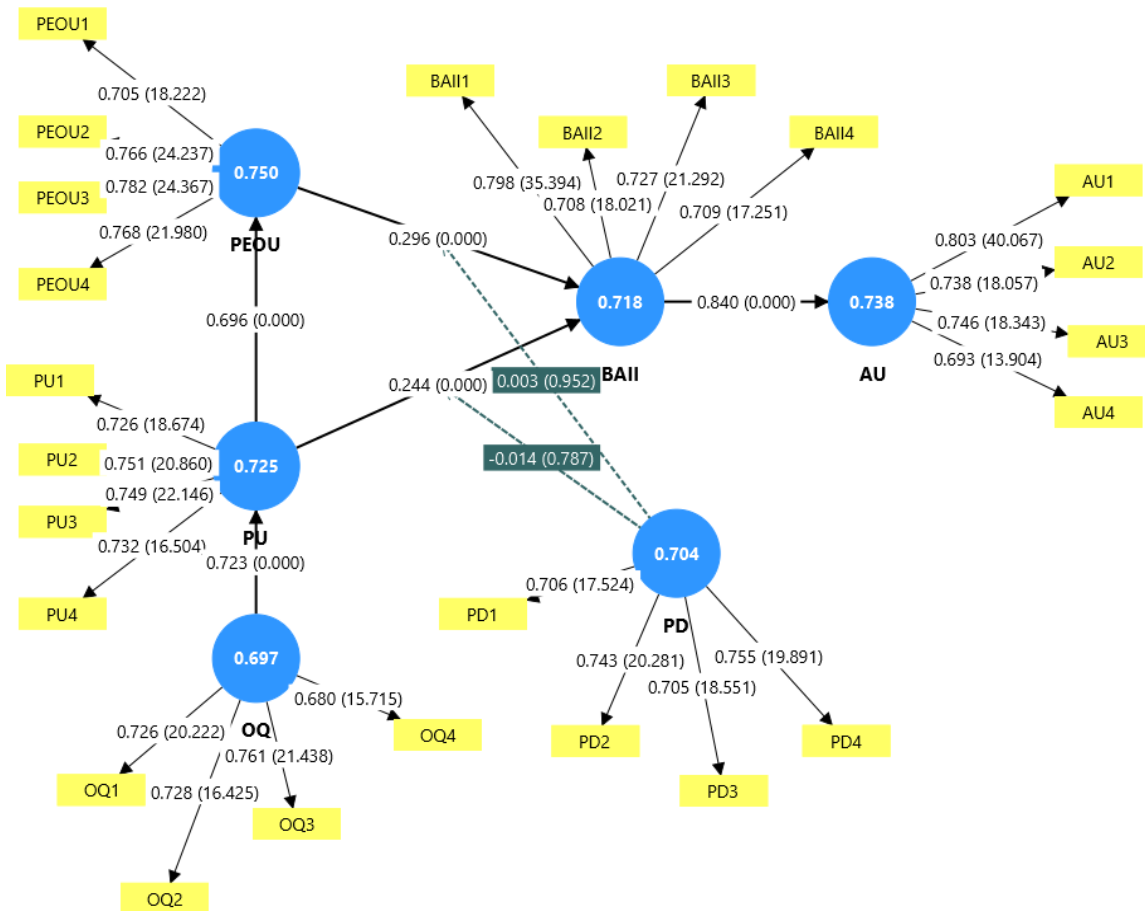


Figure 3. Structural model and PLS-SEM results

MODEL EXPLANATORY AND PREDICTIVE POWER

The explanatory power of endogenous constructs was assessed using R^2 and adjusted R^2 values, which indicate the proportion of variance explained by the model. Table 8 summarizes these results.

Table 8. R^2 and adjusted R^2 values

Construct	R^2	Adjusted R^2
AU	0.706	0.705
BAII	0.635	0.628
PU	0.523	0.521

As shown in Table 8, the model explains 70.6% of the variance in AU and 63.5% in BAII, indicating substantial explanatory power for these key outcomes. The R^2 value for PU indicates that the model explains 52.3% of its variance. Adjusted R^2 values are close to R^2 , indicating that the explained variance remains stable after accounting for the number of predictors in the model.

Table 9 presents the effect sizes (f^2) for the structural paths and the predictive relevance (Q^2) for the key endogenous constructs. Following Cohen's (1988) guidelines, $BAII \rightarrow AU$ ($f^2 = 2.397$) and $PEOU \rightarrow PU$ ($f^2 = 0.939$) have large effect sizes. $OQ \rightarrow PU$ ($f^2 = 0.296$) has a medium effect size, whereas $PD \rightarrow BAII$ ($f^2 = 0.123$), $PEOU \rightarrow BAII$ ($f^2 = 0.103$), and $PU \rightarrow BAII$ ($f^2 = 0.063$) have small effect sizes. Both moderating effects have no substantive effect size ($f^2 = 0.000$).

Table 9. Effect sizes (f^2) and predictive relevance (Q^2)

Path	f^2	Effect size
$BAII \rightarrow AU$	2.397	Large
$OQ \rightarrow PU$	0.296	Medium
$PEOU \rightarrow PU$	0.939	Large
$PD \rightarrow BAII$	0.123	Small
$PEOU \rightarrow BAII$	0.103	Small
$PU \rightarrow BAII$	0.063	Small
$PD \times PEOU \rightarrow BAII$	0.000	None
$PD \times PU \rightarrow BAII$	0.000	None

Table 10. Predictive relevance (Q^2) of endogenous constructs

Construct	Q^2
BAII	0.317
AU	0.221

Predictive relevance was assessed using Q^2 . The Q^2 values for BAII and AU were 0.317 and 0.221, respectively, as shown in Table 10. Both values exceeded zero, indicating predictive relevance for BAII and AU of AI tools. Table 11 summarizes the results of the seven hypotheses, confirming the five hypothesized direct relationships (H1–H5) and showing that the two proposed moderating effects (H6–H7) were not supported. The model also included a significant direct effect of PD on BAII.

Table 11. Hypothesis testing summary

Hypothesis	Path	β	p-value	Supported?
H1	PEOU $\rightarrow$ PU	0.696***	<0.001	Yes
H2	PU $\rightarrow$ BAI	0.244***	<0.001	Yes
H3	PEOU $\rightarrow$ BAI	0.296***	<0.001	Yes
H4	BAI $\rightarrow$ AU	0.840***	<0.001	Yes
H5	OQ $\rightarrow$ PU	0.723***	<0.001	Yes
H6	PD $\times$ PU $\rightarrow$ BAI	-0.014	0.787	No
H7	PD $\times$ PEOU $\rightarrow$ BAI	0.003	0.952	No

Note: *p < 0.05, **p < 0.01, ***p < 0.001

DISCUSSION

TECHNOLOGICAL DETERMINANTS OF AI ADOPTION

The findings confirm that PU significantly predicts BAI, consistent with prior studies on AI and educational technology adoption in higher education contexts (Bamasoud et al., 2025; Razi-ur-Rahim et al., 2026). However, PU was not the strongest direct predictor of BAI. PD had the strongest direct effect on BAI ($\beta = 0.348$), followed by PEOU ($\beta = 0.296$) and PU ($\beta = 0.244$). Thus, PU remains an important determinant of adoption intention, but the results indicate that ease of use and cultural orientation also contribute to faculty adoption decisions. Similar findings were reported by Al-Mamary and Alshammari (2026), who found that performance expectancy was a major predictor of AI chatbot adoption.

The strong effect of OQ on PU extends prior TAM2 research by emphasizing the importance of AI-specific performance characteristics. OQ had a strong positive path coefficient with PU ($\beta = 0.723$, $p < 0.001$), with a medium effect size ($f^2 = 0.296$). Venkatesh and Davis (2000) identified OQ as a determinant of PU, while the current finding suggests that perceptions of AI output quality are particularly relevant when faculty assess the usefulness of AI-driven educational assistants. This may reflect the uncertainty and variability associated with AI-generated outputs. The finding supports studies emphasizing the importance of reliability, trust, and evaluative judgment in AI adoption (Pavleska & Jerman Blažič, 2017). Similarly, Kasneci et al. (2023) noted that concerns regarding accuracy and bias significantly influence faculty attitudes toward AI systems.

PEOU also had a significant influence on BAI, with a stronger direct effect than PU ($\beta = 0.296$ vs. $\beta = 0.244$). This finding is consistent with Marangunić and Granić (2015), who examined the role of PU and PEOU in higher education technology adoption. Similar patterns were reported by Tarhini et al. (2015) and Alalwan et al. (2018), suggesting that ease of use remains relevant when professional users evaluate educational technologies. The effect size for PEOU $\rightarrow$ BAI was small ($f^2 = 0.103$), indicating that although the relationship was statistically significant, its substantive contribution was limited.

The strong relationship between BAI and AU indicates that behavioral intention is closely associated with actual use. BAI had the largest direct path coefficient in the model ($\beta = 0.840$, $p < 0.001$) and a large effect size ($f^2 = 2.397$). This finding aligns with prior AI adoption studies reporting strong intention-behavior relationships in AI-supported systems (Emon et al., 2023). The magnitude of this relationship also indicates that BAI is particularly important for understanding actual AI use among the faculty examined in this study.

CULTURAL INFLUENCE OF PD

One of the most important findings of this study is that PD directly influenced BAII but did not moderate the relationships among PU, PEOU, and BAII. PD had the largest standardized path coefficient among the predictors of BAII ($\beta = 0.348$, $p < 0.001$), although its f^2 value indicated a small effect ($f^2 = 0.123$). This finding suggests that PD is associated with overall adoption intention without significantly changing the strength of the relationships between technological perceptions and behavioral intention. A possible explanation is that PD functions as a general organizational orientation rather than a cognitive filter. Faculty in high-PD environments may be more receptive to institutionally endorsed technologies, thereby increasing baseline willingness to adopt (Daniels & Greguras, 2014; Khatri, 2009). However, this interpretation should be treated as a possible explanation because the present study did not directly measure institutional endorsement or policy influence.

The MGA results also indicated no significant differences in the structural relationships across gender groups ($p > 0.05$), suggesting that the proposed model relationships were consistent across male and female faculty members.

Another explanation may relate to the early-stage nature of AI adoption in higher education. Unlike mature technologies such as LMS platforms, AI-driven educational assistants remain relatively new, with limited institutional policies and norms. Consequently, personal evaluation may play a stronger role than organizational hierarchy. Similar observations were reported by Razi-ur-Rahim et al. (2026), who found limited influence of social factors in faculty AI adoption.

The findings refine cross-cultural TAM2 research by distinguishing between direct cultural effects and moderating cultural effects. Previous studies found PD moderation in technology adoption contexts (Alabri et al., 2020; El-Masri & Tarhini, 2017), particularly in mature systems with strong institutional structures. However, the current findings suggest that PD may directly influence adoption intention without necessarily altering the strength of the relationships among PU, PEOU, and BAII.

The nonsignificant interaction effects provide direct evidence for this distinction. The $PD \times PEOU \rightarrow BAII$ interaction was not significant ($\beta = 0.003$, $p = 0.952$, $f^2 = 0.000$), and the $PD \times PU \rightarrow BAII$ interaction was also not significant ($\beta = -0.014$, $p = 0.787$, $f^2 = 0.000$). Thus, the strength of the $PEOU \rightarrow BAII$ and $PU \rightarrow BAII$ relationships did not vary significantly with PD.

THEORETICAL CONTRIBUTIONS AND LITERATURE GAPS

This study contributes to the literature by addressing important gaps in AI adoption research within higher education. First, by empirically examining faculty adoption of AI-driven educational assistants across twelve public Saudi universities, the study provides context-specific evidence on how PU, PEOU, and OQ influence BAII and AU. This addresses the limited empirical research on AI-driven educational technologies in higher education, particularly within Middle Eastern contexts.

Second, the study demonstrates that a simplified TAM2 framework consisting of PU, PEOU, OQ, BAII, and AU provides meaningful explanatory power for faculty AI adoption. The model explained 70.6% of the variance in AU, 63.5% in BAII, and 52.3% in PU. The findings highlight the importance of retaining OQ as a distinct construct in AI contexts, given the variability and uncertainty inherent in AI-generated outputs (Bearman et al., 2024; Kasneci et al., 2023).

Third, by incorporating PD into the TAM2 framework, the study extends cross-cultural technology acceptance research. Although PD did not moderate the relationships between PU, PEOU, and BAII, its significant direct effect on BAII indicates that hierarchical culture is associated with adoption intention without significantly altering the relationships between the core technological determinants and BAII. This finding contributes to a more nuanced understanding of how cultural dimensions operate in technology adoption models.

Finally, the findings support the cross-cultural robustness of the core TAM2 relationships. PU and PEOU significantly predicted BAII, while the nonsignificant interaction effects indicated that these

relationships did not vary significantly with PD. This supports prior arguments regarding the applicability of TAM across cultural settings (Granić & Marangunić, 2019; Marangunić & Granić, 2015). Collectively, these findings contribute to the growing body of research on culturally informed AI adoption in higher education.

Theoretically, the findings refine cross-cultural TAM2 research by suggesting that cultural dimensions may influence adoption outcomes differently than previously assumed. Prior studies have often treated PD as a moderating factor that changes the strength of relationships among TAM constructs. However, the current findings indicate that, in the present model, PD appears to function more clearly as a direct predictor of adoption intention than as a moderator of the relationships between PU, PEOU, and BAI. This distinction suggests that PD does not necessarily weaken or strengthen the effects of PU or PEOU on BAI. Still, it may instead reflect a broader hierarchical orientation associated with adoption intention. Consequently, future TAM2 research should distinguish between cultural variables that operate as moderators and those that function as direct contextual determinants.

PRACTICAL IMPLICATIONS

The findings provide several practical implications for universities, policymakers, and AI developers.

Universities should prioritize demonstrating the practical usefulness of AI-driven educational assistants by emphasizing benefits such as improved teaching efficiency, grading support, and personalized feedback. Institutional endorsement by academic leaders may also increase baseline willingness to adopt in high-PD environments (Al-Hujran et al., 2015).

AI developers should focus on improving OQ by ensuring that outputs are accurate, reliable, and contextually relevant. Features that support customization and faculty control may further strengthen perceptions of usefulness (Bearman et al., 2024).

Faculty development programs should focus not only on technical training but also on demonstrating the pedagogical value of AI systems. Since PD was the strongest determinant of BAI, adoption strategies should emphasize professional and instructional benefits alongside usability.

MODEL PERFORMANCE

The model demonstrated meaningful explanatory and predictive performance across the endogenous constructs. These results indicate that the proposed framework explains a substantial proportion of variance in faculty AI adoption outcomes (Almaiah et al., 2020; Al-Mamary & Alshammari, 2026).

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Several limitations warrant acknowledgment. First, purposive sampling was used. The findings should not be interpreted as statistically representative of all faculty members in Saudi Arabian universities. The generalizability of the findings is therefore limited to populations with characteristics similar to those of the sampled institutions and respondents.

Second, data were collected via self-report questionnaires, which may introduce response bias, although Harman's single-factor test indicated no severe common method bias. Self-reported AU may also overestimate actual usage compared with system log data.

Third, the cross-sectional design limits causal inference. Longitudinal research would better establish directionality among TAM2 constructs. Fourth, the simplified TAM2 excluded SN, JR, and RD, which may become more relevant as AI tools mature. Fifth, only PD was examined, while other Hofstede dimensions (e.g., uncertainty avoidance and individualism–collectivism) were not included. Sixth, the OQ construct showed marginal reliability ($\alpha = 0.697$), suggesting the need for refinement in future studies. Finally, the Saudi higher education context may limit generalizability to other cultural settings.

Future research should address these limitations by replicating the model using probability sampling across diverse institutions and disciplines, incorporating system-log data, employing longitudinal designs, reintroducing additional TAM2 constructs, examining other cultural dimensions, refining OQ measurement, and conducting cross-cultural comparisons to test model invariance.

CONCLUSION

This study examined the adoption of AI-driven educational assistants among faculty in Saudi higher education using a simplified Technology Acceptance Model 2 framework. The results show that technological perceptions and cultural context both contribute to AI adoption. BAII had a strong positive effect on AU, indicating a strong association between behavioral intention and actual AI use. Among the direct predictors of BAII, PD had the largest effect, followed by PEOU and PU, and all three relationships were statistically significant. OQ also showed a strong positive relationship with PU, while PEOU significantly predicted PU. The findings, therefore, do not support the conclusion that PU is the dominant determinant of BAII. Rather, PU is a significant technological determinant, whereas PD and PEOU have larger direct effects on BAII in the proposed model. The effect-size results further indicate that $BAII \rightarrow AU$ and $PEOU \rightarrow PU$ had large effects, $OQ \rightarrow PU$ had a medium effect, and $PD \rightarrow BAII$, $PEOU \rightarrow BAII$, and $PU \rightarrow BAII$ had small effects.

Importantly, PD had a significant positive direct effect on BAII but did not significantly moderate the relationships between PEOU and BAII or between PU and BAII. The interaction effects were negligible. Thus, the findings suggest that PD is directly associated with adoption intention, but there is no evidence that it changes the strength of the relationships between technological perceptions and behavioral intention. The model explained a substantial proportion of the variance in AU, BAII, and PU. The positive Q^2 values for BAII and AU indicate predictive relevance. These results demonstrate meaningful explanatory and predictive performance for the proposed model in the Saudi higher education context.

The findings indicate that a combination of behavioral intention, technological perceptions, and cultural context shapes AI adoption among faculty. Improving the perceived usefulness and ease of use of AI systems, while ensuring high-quality outputs, may support adoption. However, the relative contribution of these factors differs across the structural relationships examined. The direct role of PD also suggests that cultural context should be considered when examining AI adoption in hierarchical academic environments. The absence of moderation indicates that PD does not significantly alter the effects of PU and PEOU on BAII. Future research should further examine PD using multi-group analysis to assess potential differences across faculty groups and institutional contexts. Future studies should also examine other Hofstede dimensions, such as uncertainty avoidance and individualism–collectivism, incorporate longitudinal and behavioral usage data, and test the model across different cultural and higher education settings.

DECLARATIONS:

COMPETING INTERESTS

The authors declare that they have no competing interests.

FUNDING

There is no internal or external funding for this research

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

INFORMED CONSENT

Formal written consent was not required due to the anonymous, questionnaire-based design of the study, which did not involve medical procedures or human experimentation. All participants were over 25 years old and held a BSc, a Master's degree, or a PhD. They provided implied consent by voluntarily completing the questionnaire after being informed that their responses would remain anonymous and confidential. Data were collected confidentially, anonymously, and solely for research purposes.

REFERENCES

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- Alabri, S. D., Kamaruddin, S., Gilal, A. R., Jaafar, J., & Aziz, I. A. (2020). The moderation influence of power distance on the relationship between technological factors and the successful implementation of citizen relationship management in the public sector. *IEEE Access*, 8, 132446–132465. <https://doi.org/10.1109/ACCESS.2020.3010126>
- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services*, 40, 125–138. <https://doi.org/10.1016/j.jretconser.2017.08.026>
- Al-Hujran, O., Al-Debei, M. M., Chatfield, A., & Migdadi, M. (2015). The imperative of influencing citizen attitude toward e-government adoption and use. *Computers in Human Behavior*, 53, 189–203. <https://doi.org/10.1016/j.chb.2015.06.025>
- Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the e-learning system usage during COVID-19 pandemic. *Education and Information Technologies*, 25, 5261–5280. <https://doi.org/10.1007/s10639-020-10219-y>
- Al-Mamary, Y. H. (2025). A comprehensive model for AI adoption: Analysing key characteristics affecting user attitudes, intentions and use of ChatGPT in education. *Human Systems Management*, 44(6), 978-999. <https://doi.org/10.1177/01672533251340523>
- Al-Mamary, Y. H., & Alshammari, M. M. (2026). AI chatbots for better or worse? Trust, enjoyment and ethics in AI adoption through a UTAUT lens. *Journal of Science and Technology Policy Management*. <https://doi.org/10.1108/jstpm-06-2025-0252>
- Alzahrani, H. A., Ahmad, M. T., Algarni, A. S., Althumairi, R. K., Almaker, Y. A., Alashqan, Z. S., Alqahtani, A. M., Abd El Maksoud, W. M., Bawahab, M. A., & Abbas, K. S. (2025). Assessment of physical activity levels among undergraduate medical students at a southwestern college in Saudi Arabia: A cross-sectional study. *Critical Public Health*, 35(1), 2472847. <https://doi.org/10.1080/09581596.2025.2472847>
- Amouri, H., Haroud, S., Ouchauoka, L., & Saqri, N. (2025). Acceptability of artificial intelligence in inclusive education: a TAM2-based study among preservice teachers. *Frontiers in Artificial Intelligence*, 8, 1616327. <https://doi.org/10.3389/frai.2025.1616327>
- Bamasoud, D. M., Mohammad, R., & Bilal, S. (2025). Adopting generative AI in higher education: A dual-perspective study of students and lecturers in Saudi Universities. *Big Data and Cognitive Computing*, 9(10), 264. <https://doi.org/10.3390/bdcc9100264>
- Bearman, M., Tai, J., Dawson, P., Boud, D., & Ajjawi, R. (2024). Developing evaluative judgement for a time of generative artificial intelligence. *Assessment and Evaluation in Higher Education*, 49(6), 893–905. <https://doi.org/10.1080/02602938.2024.2335321>
- Chanda, R. C., Vafaei-Zadeh, A., Hanifah, H., & Ramayah, T. (2025). Artificial intelligence teaching assistant adoption in university education: Key drivers through the ability, motivation and opportunity framework. *Education and Information Technologies*, 30, 14123–14164. <https://doi.org/10.1007/s10639-025-13360-8>
- Cheah, J.-H., Magno, F., & Cassia, F. (2024). *Reviewing the SmartPLS 4 software: The latest features and enhancements*. Springer. <https://doi.org/10.1057/s41270-023-00266-y>

- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745–783. <https://doi.org/10.1007/s10490-023-09871-y>
- Cohen, J. (1988). Set correlation and contingency tables. *Applied Psychological Measurement*, 12(4), 425–434. <https://doi.org/10.1177/014662168801200410>
- Cortez, P. M., Ong, A. K. S., Diaz, J. F. T., German, J. D., & Jagdeep, S. J. S. S. (2024). Analyzing Preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Helijon*, 10, 25896. <https://doi.org/10.1016/j.helijon.2024.e25896>
- Creswell, J. W. (2012). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (4th ed.). Pearson.
- Crompton, H., & Burke, D. (Eds.). (2024). *Artificial intelligence applications in higher education: Theories, ethics, and case studies for universities*. Routledge. <https://doi.org/10.4324/9781003440178>
- Daniels, M. A., & Greguras, G. J. (2014). Exploring the nature of power distance: Implications for micro-and macro-level theories, processes, and outcomes. *Journal of Management*, 40(5), 1202–1229. <https://doi.org/10.1177/0149206314527131>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, 13(3). <https://doi.org/10.2307/249008>
- Dirgiamto, Y. (2023). Testing the discriminant validity and Heterotrait-Monotrait ratio of correlation (HTMT): A case in Indonesian SMEs. In W. A. Barnett & B. S. Sergi (Eds.), *Macroeconomic risk and growth in the South-east Asian Countries: Insight from Indonesia* (pp. 157–170). Emerald Publishing. <https://doi.org/10.1108/S1571-03862023000033A011>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, Article 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Eisenberg, R. L., Cunningham, M. L., Siewert, B., & Kruskal, J. B. (2014). Survey of faculty perceptions regarding a peer review system. *Journal of the American College of Radiology*, 11(4), 397–401. <https://doi.org/10.1016/j.jacr.2013.08.011>
- El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). *Educational Technology Research and Development*, 65(3), 743–763. <https://doi.org/10.1007/s11423-016-9508-8>
- Emon, M. M. H., Hassan, F., Nahid, M. H., & Rattanawiboonsom, V. (2023). Predicting Adoption Intention of Artificial Intelligence - A Study on ChatGPT. *AIUB Journal of Science and Engineering*, 22(2), 189–199. <https://doi.org/10.53799/AJSE.V22I2.797>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Ghaleb, E. A. A., Dominic, P. D. D., Fati, S. M., Muneer, A., & Ali, R. F. (2021). The assessment of big data adoption readiness with a technology–organization–environment framework: a perspective towards healthcare employees. *Sustainability*, 13(15), 8379. <https://doi.org/10.3390/su13158379>
- Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, 50(5), 2572–2593. <https://doi.org/10.1111/bjet.12864>
- Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), Article 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. F., Jr., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110. <https://doi.org/10.1016/j.jbusres.2019.11.069>

- Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage. <https://www.sagepub.com/shop/buy-a-book/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem-3-270548>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations*. Sage.
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Khatri, N. (2009). Consequences of power distance orientation in organisations. *Vision*, 13(1), 1–9. <https://doi.org/10.1177/097226290901300101>
- Li, M., & Rasiyah, R. (2025). High-performance work systems, psychological empowerment, and power distance orientation in shaping employee innovation, a moderated mediation model. *Scientific Reports*, 15, Article 27189. <https://doi.org/10.1038/s41598-025-08522-0>
- López-Costa, M., Donate-Bebby, B., Cabrera-Lanzo, N., & Maina, M. F. (2025). Understanding AI adoption among secondary education teachers: A pls-sem approach. *Computers and Education: Artificial Intelligence*, 8, Article 100416. <https://doi.org/10.1016/j.caeai.2025.100416>
- Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, 14, 81–95. <https://doi.org/10.1007/s10209-014-0348-1>
- Marian, A.-L., Apostolache, R., & Ceobanu, C. M. (2025). Toward sustainable technology use in education: Psychological pathways and professional status effects in the TAM framework. *Sustainability*, 17(15), 7025. <https://doi.org/10.3390/su17157025>
- Ministry of Education. (2024). *Higher education statistics: Faculty members in Saudi universities*. Kingdom of Saudi Arabia. <https://moe.gov.sa/en/knowledgecenter/dataandstats/pages/opendata.aspx>
- Pavleska, T., & Jerman Blažič, B. (2017). User bias in online trust systems: aligning the system designers' intentions with the users' expectations. *Behaviour & Information Technology*, 36(4), 404–421. <https://doi.org/10.1080/0144929X.2016.1239761>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Razi-ur-Rahim, M., Uddin, F., Chauhan, J., & Faisal, K. P. (2026). GenAI in Indian higher education: faculty at the crossroads of adoption. *Asian Education and Development Studies*, 15(1), 41–72. <https://doi.org/10.1108/AEDS-04-2025-0194>
- Ringle, C. M., Wende, S., & Becker, J. M. (2024). *SmartPLS 4*. SmartPLS.
- Rogers, E. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
- Shanghai Ranking. (2025). *Academic ranking of world universities 2025*. <https://www.shanghairanking.com/rankings/arwu/2025>
- Syed, A. Z., Memon, Z. H., Khan, K., Hameed, I., & Nadeem, M. (2025). Examining the behavioral determinants of AI adoption in higher education: a focus on perceptual factors and demographic differences. *On the Horizon: The International Journal of Learning Futures*, 33(2), 245–264. <https://doi.org/10.1108/OTH-02-2025-0019>
- Tarhini, A., Hone, K., & Liu, X. (2015). A cross-cultural examination of the impact of social, organisational and individual factors on educational technology acceptance between British and Lebanese university students. *British Journal of Educational Technology*, 46(4), 739–755. <https://doi.org/10.1111/bjiet.12169>

- Tran, P. T., & Nguyen, D. T. (2024). Behavioral intention to adopt artificial intelligence for teaching in higher education: A case study in Vietnam. *Journal of Computer Science and Technology Studies*, 6(2).
- Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology*, 52(5), 463–479. <https://doi.org/10.1016/j.infsof.2009.11.005>
- Vashishth, T. K., Sharma, V., Sharma, K. K., & Kumar, B. (2024). The future of higher education: Using AI in universities to improve learning outcomes and operational efficiency. In S. Tripathi & J. Rosak-Szyrocka (Eds.), *Impact of artificial intelligence on society* (pp. 60–80). Chapman and Hall/CRC. <https://doi.org/10.1201/9781032644509-5>
- Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2025). Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy. *International Journal of Human-Computer Interaction*, 41(11), 6649–6671. <https://doi.org/10.1080/10447318.2024.2383033>
- Yoo, B., Donthu, N., & Lenartowicz, T. (2011). Measuring Hofstede's five dimensions of cultural values at the individual level: Development and validation of CVSCALE. *Journal of International Consumer Marketing*, 23(3–4), 193–210. <https://doi.org/10.1080/08961530.2011.578059>

APPENDIX. COMPLETE SURVEY INSTRUMENT AND MEASUREMENT ITEMS

Construct	Code	Measurement item	Adapted from
Perceived Ease of Use (PEOU)	PEOU1	Learning to use AI-driven educational assistants is easy for me.	Davis (1989)
	PEOU2	Interacting with AI-driven educational assistants is clear and understandable.	Davis (1989)
	PEOU3	I find AI-driven educational assistants easy to use in my teaching activities.	Davis (1989)
	PEOU4	It is easy for me to become skillful at using AI-driven educational assistants.	Davis (1989)
Perceived Usefulness (PU)	PU1	Using AI-driven educational assistants improves my teaching performance.	Davis (1989); Venkatesh and Davis (2000)
	PU2	AI-driven educational assistants enhance my teaching effectiveness.	Davis (1989); Venkatesh and Davis (2000)
	PU3	AI-driven educational assistants increase my productivity in academic tasks.	Davis (1989); Venkatesh and Davis (2000)
	PU4	Overall, AI-driven educational assistants are useful for my teaching responsibilities.	Davis (1989); Venkatesh and Davis (2000)

Construct	Code	Measurement item	Adapted from
Output Quality (OQ)	OQ1	AI-generated outputs are accurate.	Venkatesh and Bala (2008)
	OQ2	AI-generated outputs are reliable for academic tasks.	Venkatesh and Bala (2008)
	OQ3	AI-driven educational assistants provide high-quality outputs.	Venkatesh and Bala (2008)
	OQ4	The outputs generated by AI systems meet my teaching needs.	Modified from Venkatesh and Bala (2008)
Behavioral Adoption Intention (BAII)	BAII1	I intend to use AI-driven educational assistants regularly in the future.	Venkatesh et al. (2003)
	BAII2	I will frequently use AI-driven educational assistants in my teaching activities.	Venkatesh et al. (2003)
	BAII3	I plan to integrate AI-driven educational assistants into my courses.	Modified from Venkatesh et al. (2003)
	BAII4	I would recommend AI-driven educational assistants to other faculty members.	Cortez et al. (2024)
Actual Use (AU)	AU1	I frequently use AI-driven educational assistants in teaching-related tasks.	Emon et al. (2023)
	AU2	I use AI tools to support content preparation or grading.	Modified from Emon et al. (2023)
	AU3	AI-driven educational assistants are integrated into my teaching workflow.	Emon et al. (2023)
	AU4	I rely on AI-driven educational assistants for academic support activities.	Modified from Emon et al. (2023)
Power Distance (PD)	PD1	Faculty members should follow institutional directives regarding technology adoption.	Hofstede (2001)
	PD2	Decisions made by university leadership regarding AI adoption should be accepted by faculty.	Modified from Hofstede (2001)
	PD3	Hierarchical authority influences my willingness to adopt AI technologies.	Modified from Hofstede (2001)
	PD4	Faculty members are expected to comply with institutional technology policies.	Hofstede (2001)

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