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Factors Affecting Lecturers' Intention to Adopt Artificial Intelligence Tools for Assessing Students' Performance in Malaysian Universities

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ABSTRACT

Empowering the student assessment process in higher education through artificial intelligence has become essential for delivering more adaptive, accurate, and equitable evaluations in a rapidly evolving educational landscape. As Malaysia seeks to integrate such technology into its assessment practices, lecturers' support and willingness are essential for successful implementation. Thus, this research investigates the factors influencing lecturers' intentions to adopt AI-based assessment tools in Malaysian universities by extending the meta-analysis based Modified Unified Theory of Acceptance and Use of Technology (meta-UTAUT). Data were collected from 414 lecturers in the Klang Valley and analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that performance expectancy, effort expectancy, self-efficacy, trust, compatibility, and personal innovativeness influence lecturers' attitudes. For adoption intention, performance expectancy, self-efficacy, personal innovativeness, and attitude are key predictors. Moreover, lecturers' attitudes mediate the relationships between performance expectancy, effort expectancy, self-efficacy, trust, compatibility, and personal innovativeness and their intention. This study offers novel insights into AI-based assessment adoption and represents the first empirical application of the meta-UTAUT model in this context. From a practical perspective, the findings provide actionable guidance for policymakers, administrators, and developers to support the effective implementation of these tools in Malaysian universities.

Keywords: Assessment, Artificial intelligence, Higher education, Meta-UTAUT, Technology adoption, Intelligent teaching and learning, Student performance

1. Introduction

Artificial intelligence (AI) in higher education (HE) has reshaped teaching and learning (T/L) by enhancing effectiveness, adaptability, and overall quality (Chassab et al., 2021). It enables adaptive learning, provides immediate feedback, supports progress monitoring with early necessary interventions, and streamlines administrative tasks, thereby allowing lecturers to focus on other activities (Baker et al., 2019). These benefits encourage universities to adopt AI technologies to stay competitive and enhance the student learning experience (Naji et al., 2022). However, successful implementation heavily depends on lecturers' support, as they are the key stakeholders in HE (Wang et al., 2021). Thus, recent studies have examined factors influencing lecturers' acceptance and adoption of AI technologies using different models. For example, the

Unified Theory of Acceptance and Use of Technology (UTAUT) has been employed to examine learning analytics usage (Herodotou et al., 2023), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) has been applied to investigate ChatGPT usage (Strzelecki et al., 2024), the Innovation Diffusion Theory has been used to study the adoption of intelligent tutoring systems (Wang et al., 2020), and the Technology Acceptance Model (TAM) has been adopted to explore the adoption of AI-based applications (Wang et al., 2021). Student assessment is a cornerstone of the educational process, and Malaysian universities are enhancing it through AI, enabling evaluations that are faster, more accurate, and more authentic than traditional methods (Ishaq et al., 2020). Thus, this study aims to investigate factors influencing lecturers' intentions to adopt AI assessment tools (AIAT) in Malaysian universities. The structure of this article is as follows: Section 2 reviews the current assessment process, AI in the assessment process and its adoption in Malaysia, and the development of the proposed model. Section 3 describes the methodology, and Section 4 presents the results. Section 5 provides the discussion, followed by the study's contributions and limitations in Sections 6, 7, 8, respectively. Finally, the conclusions are presented in Section 9.

2. Literature Review

2.1. Assessment Process

Student assessment plays a central role in HE by measuring learning outcomes and informing instructional practices (Akil & Matore, 2023). Effective assessment is closely linked to student satisfaction, motivation for academic achievement, and successful academic progression (Rigopoulos, 2022). Despite its importance, the literature consistently highlights several limitations associated with traditional assessment systems. Mainly, assessment practices in many universities remain largely summative and end-of-course oriented rather than being embedded throughout the learning process (Camacho-Miñano et al., 2020). Such an approach provides isolated snapshots of performance rather than a holistic view of learning, failing to capture the dynamic and continuous nature of learning (IIUM, 2015). In addition, concentrating assessments at the end of a course imposes a time constraint for both students and faculty. This limitation reduces students' ability to consolidate learning, engage deeply with the material, and manage stress and anxiety effectively (Braga et al., 2024). It also pressures faculty to prepare students for examinations within a limited timeframe, leading to "teaching to the exam," which hinders the development of a dynamic learning environment (Braga et al., 2024). Such assessment methods are also inadequate for accurately measuring students' understanding and capabilities (Braga et al., 2024).

Equally important, the rigidity of traditional assessment methods limits their capacity to adapt to rapid curricular changes, technological advancements, and evolving educational needs (Ali, 2024). Traditional assessments often possess a narrow scope and may struggle to ensure consistent, valid, and reliable measurement of learning outcomes across diverse contexts (Song, 2024). Moreover, approaches such as standardised tests frequently emphasise rote memorisation and basic cognitive abilities; failing to capture higher-order skills, such as creativity, critical thinking, collaboration, and problem-solving, that are essential for real-world applications (Ali, 2024). The emergence of generative AI tools, such as ChatGPT, further challenges conventional assessment practices, as students may exploit these technologies to submit non-original work, raising concerns regarding authentic assessment, academic integrity, and the credibility of higher education outcomes (Smolansky et al., 2023).

Another significant challenge in academic assessment is evaluation bias, which can distort student performance based on personal characteristics such as gender, ethnicity, or socioeconomic status (Ali, 2024). Bias may also emerge from subjective judgments when different educators evaluate the same assignment, leading to inconsistencies in grading. Uniform assessment approaches that fail to account for students' diverse prior knowledge, abilities, learning experiences, or cultural backgrounds can further disadvantage some students, limiting their capacity to demonstrate true skills and creating an unequal playing field (Smolansky et al., 2023).

Moreover, assessment is often perceived as burdensome, time-consuming, and complex for educators to design and implement effectively (Flodén, 2024). Limited human resources and teacher-centred approaches exacerbate this issue, with approximately 40% of educators' time devoted to grading and related tasks (Kamalov et al., 2023). Assessment quality may also be compromised by repetitive grading, fatigue, and subjective influences, including an educator's mood, particularly in large cohorts (Ye & Manoharan, 2018). Even widely used computer-based systems primarily support objective-type questions (e.g., multiple-choice) and are not designed to assess descriptive or higher-order responses such as essays (Pinto et al., 2023). Consequently, current assessment practices, manual or semi-automated, remain costly, error-prone, and increasingly inflexible (Machicao, 2019).

The digital era has further exposed the limitations of traditional methods, as AI tools facilitate cheating and misrepresentation of skills, raising concerns about the accuracy and integrity of student evaluation (AIBIG, 2024). As a result, these challenges underscore the urgent need for authentic assessment strategies and systematic reform to maintain the accuracy and integrity of student evaluation while keeping pace with technological advancements.

2.2. Adopting AI-based Assessment Tools in Malaysia

AI is transforming assessment and grading by addressing the limitations of traditional methods and enabling immediate, more precise, and inclusive evaluation practices suited to the evolving educational landscape (Bond et al., 2024). Unlike conventional grading, which is constrained by human limitations, intelligent assessment technologies analyze student responses in real time and provide instant feedback (Onesi-Ozigagun et al., 2024). In large-enrolment courses, these systems can reduce grading time by 30–60% (Alfaleh, 2026). AI technologies also facilitate the adaptation of traditional assessment methods to support the continuous evaluation of student performance across courses, offering deeper insights into learning progress (Sporrong et al., 2025). This enables students to identify their strengths and weaknesses more rapidly, thereby enhancing learning outcomes (Strielkowski et al., 2025). In addition, such capabilities allow instructors to detect learning gaps at an earlier stage and provide timely interventions, helping students remain on track and achieve their academic goals (Onesi-Ozigagun et al., 2024).

AI systems can further enhance the reliability and validity of assessments while reducing errors and biases associated with manual grading by applying standardized evaluation procedures through algorithmic models (Xia et al., 2024). These systems can efficiently evaluate complex student work, including written and verbal responses, particularly in classes with large numbers of students (Alfaleh, 2026). In the same vein, adaptive AI-based assessments dynamically adjust question difficulty according to students' abilities, providing tailored assessment experiences that improve accuracy and fairness while maintaining appropriate levels of challenge (Khlaif et al., 2024). This indicates that AIAT functions not only as tools for improving efficiency but also as a mechanism for delivering genuinely personalized assessments, thereby overcoming the limitations of traditional "one-size-fits-all" examinations.

Furthermore, the integration of AI content detection tools, such as Writer, Copyleaks, GPTZero, and CrossPlag, marks a shift in enforcing academic integrity. Rather than serving solely as punitive mechanisms, these tools support a broader move toward AI-aware pedagogy (Deep et al., 2025). By automating originality checks, institutions can address challenges posed by generative AI while reinforcing academic standards. This shifts the focus from merely detecting misconduct to promoting transparent and ethical AI use, helping maintain academic integrity in an increasingly technology-driven learning environment (Deep et al., 2025). Ultimately, by leveraging AIAT, HE institutions can move toward a continuous assessment model. This provides a more holistic view of student progress than traditional high-stakes exams, which only capture a single point in time (Onesi-Ozigagun et al., 2024). Examples of AIAT currently available include ChatGPT, Smodin's AI Grader, Moodie.ai, and Noodle Factor.

Malaysia's strategic landscape for AI integration is characterized by a robust, top-down push through initiatives, such as the Malaysia Education Blueprint 2015–2025 (Higher Education), MyDIGITAL, and the National Artificial Intelligence Roadmap 2021-2025 (MOSTI, 2021; National AI Office, 2021, 2025). Despite these policies, a significant gap exists between the national vision and its implementation in universities. AIAT adoption remains fragmented and reactive, constrained by differences in governance, faculty readiness, and technological infrastructure (Osman et al., 2024). This policy-practice gap, where strategic ambition exceeds institutional capacity, reflects a common challenge in emerging AI education contexts (Saman et al., 2024) and highlights that adoption involves complex human and organizational factors. At the core of this challenge are lecturers, who serve as the ultimate gatekeepers of pedagogical innovations. Their behavioral intention to adopt new technologies is the crucial factor determining the successful integration of AIAT into practice (Wang et al., 2021). While AIAT offers great opportunities to improve assessment, it also raises ethical and pedagogical concerns, including potential neglect of core educational values and reduced human involvement, or "human stunting" (Sporrong et al., 2025). Resistance may also arise from perceived complexity, unfamiliarity, or fundamental doubts about the pedagogical value of these tools (Zhai et al., 2021).

To better understand lecturers' intentions to adopt AIAT, different technology adoption models have been applied and extended in prior research. For example, Sánchez-Prieto et al. (2019) proposed an extended TAM model that incorporates factors such as trust, AI anxiety, and relative advantage. Shahid et al. (2024) adapted UTAUT and revealed that anxiety and adoption readiness significantly influence lecturers' attitudes toward AIAT adoption. Despite these valuable contributions, empirical research on AIAT adoption in HE remains limited. The specific challenges and enabling factors that shape lecturers' adoption decisions are still not fully understood, particularly within specific contexts. Moreover, some studies have focused primarily on attitudes as the key outcome variable, overlooking behavioural intention as the immediate predictor of actual use. In contrast, research on AI adoption in other sectors suggests that behavioural intention is influenced by a range of domain-specific factors. In service contexts, behavioral intention is influenced by psychological traits, perceived empathy, risk, satisfaction, and interaction quality (Meidute-Kavaliauskiene et al., 2021; Pillai et al., 2020; Seo & Lee, 2021). In healthcare, perceived usefulness and subjective norms are key determinants (So et al., 2021), while in finance, trust and religiosity are significant predictors (Alkhowaiter, 2022). Similarly, studies in management contexts highlight the influence of performance expectancy, effort expectancy, facilitating conditions, satisfaction, and system quality (Chatterjee et al., 2021). Although these studies offer valuable insights into AI adoption, they often overlook the unique challenges of adopting AIAT in higher education, such as academic integrity, ethical considerations, and alignment with institutional policies. Addressing this gap is essential to translate policy objectives into effective, sustainable practices that enhance learning outcomes while maintaining academic integrity. Based on the discussion above, this study investigates the factors influencing lecturers' intentions to adopt AIAT in Malaysian universities. Specifically, the study addresses the following research questions:

RQ1: What are the key factors that influence lecturers' intentions to adopt AIAT in Malaysian universities?

RQ2: How can these factors be integrated into a theoretical model to explain lecturers' intentions to adopt AIAT?

RQ3: To what extent is the proposed model valid and reliable in explaining lecturers' intentions to adopt AIAT?

2.3. Research Model and Development of Hypotheses

To address RQ1, we critically evaluated the prominent technology adoption models based on logical consistency, scope, explanatory power, and parsimony (Bhattacherjee, 2012). This comparative analysis was essential given the scarcity of empirical research on AIAT. While foundational models like the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991), TAM, and Model of PC Utilization (MPCU) (Thompson et al., 1991) offer consistency, they prove insufficient for the multi-dimensional nature of AIAT. Specifically, TRA and TPB focus almost exclusively on psychological determinants, neglecting environmental and organizational influences, while TAM lacks social dimensions, and MPCU is restricted to personal computer use. The evaluation further indicates that the Technology Acceptance Model 2 (TAM2) (Venkatesh & Davis, 2000) and the Technology Acceptance Model 3 (TAM3) (Venkatesh & Bala, 2008) neglects the direct impact of external factors on intention, whereas UTAUT overlooks the relationship between facilitating conditions and behavioral intention. Notably, UTAUT and its extensions (i.e., UTAUT2 and UTAUT3) omit the mediating role of attitude, which is a factor identified as vital during early adoption stages (Upadhyay et al., 2022). Furthermore, Social Cognitive Theory (SCT) (Compeau et al., 1999) introduces interpretive ambiguity and fails to capture IT-specific determinants, such as facilitating conditions. Neglecting these factors and relationships would provide a reductionist view of technology adoption, overlooking the enablers and barriers that ultimately determine the successful integration of AIAT in Malaysia. Additionally, it would reduce explanatory power, as models such as TRA, TPB, TAM, MPCU, and SCT have frequently been shown to explain a low proportion of variance in complex environments (Bellet & Banet, 2023). Even UTAUT demonstrates relatively low predictive power when applied to academic staff, with explained variance ranging between 17% and 35% (Gunasinghe et al., 2020). From a parsimony perspective, while simpler models (e.g., TPB and TAM) are easy to apply, complex models, such as TAM3 or the full SCT, are difficult to operationalize (Daniel Mehari Alemayehu, 2023) or rely on moderators that lack universal relevance (i.e., UTAUT and UTAUT2) (Dwivedi et al., 2020).

The meta-UTAUT model (Dwivedi et al., 2019) addresses these limitations and is therefore adopted as the theoretical foundation for this study. It incorporates attitude as a mediating construct, providing a balanced structure that integrates individual, social, contextual, and technological dimensions relevant to technology adoption. This configuration offers the necessary theoretical depth for explaining technology adoption within educational contexts (Kannan et al., 2018). Furthermore, the inclusion of attitude enhances the model's explanatory power, while the removal of moderating variables simplifies its structure (Hakim et al., 2023), thereby improving its applicability for examining lecturers' intentions to adopt AIAT.

Dwivedi et al. (2020) recommended extending the meta-UTAUT model with context-specific factors to provide a more comprehensive representation of the phenomenon under investigation. In line with this recommendation, this study conducted a systematic review of 919 studies indexed in Scopus and Web of Science that cited the original model (Dwivedi et al., 2019). Studies were included if they used meta-UTAUT as their theoretical foundation and incorporated external factors. As presented in Table 1, 12 studies met these criteria, collectively forming a pool of 21 potential external factors.

Source	Purpose	External factors and their relationships
Alkhowaiter (2022)	Developed and validated a model to investigate the factors affecting the use of mobile payments	Trust → intention
Upadhyay et al. (2022)	Developed and validated a model examining factors influencing consumer adoption of mobile payment services during COVID-19	Self-efficacy → effort expectancy Perceived severity → attitude
Balakrishnan et al. (2022)	Developed and validated a model that investigates the factors influencing users to adopt chatbots in services	Perceived intelligence → attitude and intention Perceived anthropomorphism → attitude and intention Social self-efficacy moderates the relationships between variables and intention
Hermanto et al. (2022)	Developed and validated a model that examines the factors impacting taxpayers' adoption of online tax return reporting	Trust → attitude Grievance redressal moderates the relationship between facilitating conditions and intention
Chatterjee et al. (2021)	Proposed a model to examine the factors influencing organizational users' adoption of AI-based CRM systems	Compatibility → attitude and intention CRM satisfaction → attitude and intention CRM quality → attitude and intention Attitude as a mediator between all variables and intention
Roy et al. (2021)	Develop and validate a model to investigate the factors affecting customer engagement behaviour in smart retailing	SRT novelty → performance expectancy, effort expectancy, social influence, and facilitating conditions SRT effectiveness → performance expectancy, effort expectancy, social influence, and facilitating conditions SRT interaction quality → performance expectancy, effort expectancy, social influence, and facilitating conditions Attitude as a mediator between UTAU variables and engagement
Tamilmani et al. (2022)	Developed and validated a model to investigate the factors influencing consumers' intentions to use Airbnb	Self-efficacy → intention Trust → intention Hedonic motivation → effort expectancy Attitude as a mediator between UTAUT variables and intention
Sarker et al. (2020)	Proposed a model to identify the factors influencing consumer adoption of social commerce	Trust → intention Perceived risk → intention
Patil et al. (2020)	Developed and validated a model that examines the factors impacting the adoption of consumer mobile payments	Personal innovativeness → attitude Anxiety → attitude Trust → attitude Attitude as a mediator between all variables and intention
Wiafe et al. (2020)	Developed and validated a model to investigate the factors affecting a multi-carrier booking and shipping system usage	Self-efficacy → intention Anxiety → intention
Huseynov and Özkan Yıldırım (2019)	Developed and validated a model to examine the factors affecting consumers' shopping behaviours on B2C e-commerce platforms	Perceived enjoyment → attitude and intention Compatibility → attitude, intention, and performance expectancy Perceived information security → attitude Perceived social pressure → attitude and intention

Hossain et al. (2019)	Developed and validated a model examining factors influencing physicians' adoption of e-health records	Personal innovativeness → intention Resistance to change → intention

Table 1. Summary of the final selected studies that adapted the meta-UTAUT model

To answer RQ2, the conceptual research model was developed by extending the meta-UTAUT model with selected external factors identified through the systematic review. At this stage, maintaining a balance between parsimony and comprehensiveness was critical (Sekaran & Bougie, 2016); therefore, the most frequently cited factors across the reviewed studies were prioritized. The prevalence of these factors suggests that they effectively address the limitations of meta-UTAUT, while their widespread application in AI-related research confirms their specific relevance to the present study. Ultimately, five external factors were integrated into the meta-UTAUT model, as illustrated in Figure 1.

As a critical step in the model's development, the initial conceptual model was evaluated by 10 experts through semi-structured interviews. This evaluation yielded strong consensus on the model's validity, confirming the inclusion of all proposed factors and relationships. Based on the recommendations of two experts, the model was refined by adding a link between self-efficacy and attitude and testing the mediating effect. The definitions of the factors with their corresponding hypotheses for the model are presented below.

Performance expectancy: is the degree to which a lecturer believes that using AIAT would facilitate and improve performance assessment, enhance learning outcomes, and improve teaching quality (Venkatesh et al., 2003). Performance expectancy positively influences faculty members' intention to adopt AI (Ghimire et al., 2024). Similarly, it positively shapes employees' attitudes towards AI-based CRM systems, with attitude serving as a mediating factor between performance expectancy and intention (Chatterjee et al., 2021). Thus, we proposed the following hypotheses:

H1: Performance expectancy has a positive effect on lecturers' attitudes towards adopting AIAT.

H2: Performance expectancy has a positive effect on lecturers' intention to adopt AIAT.

H3: Lecturers' attitudes mediate the relationship between performance expectancy and their intentions to adopt AIAT.

Effort expectancy: is the degree to which a lecturer believes that AIAT would be easy to use (Venkatesh et al., 2003). Effort expectancy positively influenced users' intention to accept intelligent systems (Wanner et al., 2022). Likewise, it positively influences users' intention to adopt AI in HE, with attitude mediating the relationship between effort expectancy and adoption intention (Chatterjee & Bhattacharjee, 2020). Accordingly, we proposed the following hypotheses:

H4: Effort expectancy has a positive effect on lecturers' attitudes towards adopting AIAT.

H5: Effort expectancy has a positive effect on lecturers' intention to adopt AIAT.

H6: Lecturers' attitudes mediate the relationship between effort expectancy and their intention to adopt AIAT.

Social influence: is the degree to which a lecturer perceives that important people, such as colleagues, supervisors, or the university, expect him/her to use AIAT (Venkatesh et al., 2003). Social influence positively affects users' intention to adopt learning analytics in universities (Bahari et al., 2023) and shapes students' attitudes towards MOOCs (Altalhi, 2021). Users' attitudes towards robo-advisors mediate the relationship between social influence and intention (Roh et al., 2023). Thus, we proposed the following hypotheses:

H7: Social influence has a positive effect on lecturers' attitudes towards adopting AIAT.

H8: Social influence has a positive effect on lecturers' intention to adopt AIAT.

H9: Lecturers' attitudes mediate the relationship between social influence and their intention to adopt AIAT.

Facilitating conditions: refer to the extent to which a lecturer perceives that organizational and technical support is available for using AIAT (Venkatesh et al., 2003). The adoption of AIAT depends on adequate resources (e.g., internet access, equipment), training, and IT support, which institutions must provide to foster positive attitudes and encourage adoption (Chatterjee & Bhattacharjee, 2020). Facilitating conditions positively influence users' intention to adopt AI in HE (Chatterjee & Bhattacharjee, 2020). Additionally, they shape positive attitudes towards robo-advisors, with attitude acting as a mediating factor between facilitating conditions and adoption intention (Roh et al., 2023). Accordingly, we proposed the following hypotheses:

H10: Facilitating conditions have a positive effect on lecturers' attitudes towards adopting AIAT.

H11: Facilitating conditions have a positive effect on lecturers' intention to adopt AIAT.

H12: Lecturers' attitudes mediate the relationship between facilitating conditions and their intention to adopt AIAT.

Self-efficacy: refers to the extent to which lecturers believe in their ability to use AIAT in the future (Venkatesh et al., 2003). It affects their engagement, effort, emotional responses, and persistence in overcoming challenges (Compeau & Higgins, 1995). Low self-efficacy can hinder engagement with a new system, limiting its success, while high self-efficacy has the opposite effect (Compeau & Higgins, 1995). Self-efficacy positively influences lecturers' intention to adopt AI in HE (Wang et al., 2021). Similarly, it shapes students' attitudes towards AI-based healthcare solutions, with attitude serving as a mediator (Kwak, Ahn, et al., 2022). In addition, it enhances perceptions of effort expectancy in adopting AI-based education systems (Altalhi, 2021). Therefore, the proposed hypotheses are:
H13: Self-efficacy has a positive effect on lecturers' attitudes towards adopting AIAT.
H14: Self-efficacy has a positive effect on lecturers' intention to adopt AIAT.
H14a: Self-efficacy has a positive effect on effort expectancy regarding AIAT.
H15: Lecturers' attitudes mediate the relationship between self-efficacy and their intention to adopt AIAT.

Anxiety: is defined as a lecturer's apprehension or fear of using AIAT to assess students' performance (Venkatesh et al., 2003). Such anxiety can reduce lecturers' engagement with AI tools, leaving them unmotivated, regardless of their potential benefits (Gupta & Bhaskar, 2020). Anxiety negatively influences users' intention to adopt AI-enabled tools (Kleine et al., 2023). In addition, it influences students' attitudes towards AI-based healthcare systems, with attitude serving as a mediating factor between anxiety and intention (Kwak, Seo, et al., 2022). Thus, the following hypotheses are proposed:
H16: Anxiety has a negative effect on lecturers' attitudes towards adopting AIAT.
H17: Anxiety has a negative effect on lecturers' intention to adopt AIAT.
H18: Lecturers' attitudes mediate the relationship between anxiety and their intention to adopt AIAT.

Trust: refers to the extent to which lecturers believe that AIAT will meet their expectations when assessing student performance (Patil et al., 2020). Trust plays a fundamental role in shaping behaviour (Kim & Prabhakar, 2004). Low trust may lead to non-use of technology, whereas high trust can increase the risk of misuse or abuse (Parasuraman & Riley, 1997). Trust positively influences both users' attitudes and intentions to adopt robo-advisors, with attitude as a mediator (Roh et al., 2023). Thus, the proposed hypotheses are:
H19: Trust has a positive effect on lecturers' attitudes towards adopting AIAT.
H20: Trust has a positive effect on lecturers' intention to adopt AIAT.
H21: Lecturers' attitudes mediate the relationship between trust and their intention to adopt AIAT.

Compatibility: refers to the degree to which lecturers believe that adopting and using AIAT aligns with their needs, existing knowledge, assessment methods, pedagogical practices, and work tasks (Moore & Benbasat, 1991). The perceived alignment between AIAT and lecturers' perceptions is critical for driving adoption (Gupta & Bhaskar, 2020). Compatibility positively influences users' intentions to adopt smart devices (Yang et al., 2022). Moreover, it affects employees' attitudes towards AI-based CRM systems, with attitude mediating the relationship between compatibility and intention (Chatterjee et al., 2021). Furthermore, compatibility strongly predicts performance expectancy by shaping users' perceptions of efficiency and the value of AI tools (Lee & Pan, 2023). Thus, the proposed hypotheses are:
H22: Compatibility has a positive effect on lecturers' attitudes towards adopting AIAT.
H23: Compatibility has a positive effect on lecturers' intention to adopt AIAT.
H23a: Compatibility has a positive effect on the performance expectancy of AIAT.
H24: Lecturers' attitudes mediate the relationship between compatibility and their intention to adopt AIAT.

Personal innovativeness: refers to the extent to which a lecturer is willing to try new technologies, such as AIAT (Agarwal & Prasad, 1998). Highly innovative lecturers drive technology adoption, as they are more receptive to change and confident in integrating AI-based tools to enhance T/L (Gupta & Bhaskar, 2020). Personal innovativeness has a positive effect on users' intention to adopt AI tools in HE (Bahari et al., 2023) and positively influenced users' attitudes towards using AI tools (Wang & Dai, 2020). Moreover, users' attitudes mediate the relationship between personal innovativeness and intention to adopt mobile payment (Patil et al., 2020). Hence, we proposed the following hypotheses:
H25: Personal innovativeness has a positive effect on lecturers' attitudes towards adopting AIAT.
H26: Personal innovativeness has a positive effect on lecturers' intention to adopt AIAT.
H27: Lecturers' attitudes mediate the relationship between personal innovativeness and their intention to adopt AIAT.

Attitude towards using AIAT: refers to a lecturer's positive or negative disposition towards using AIAT for student assessment (Venkatesh et al., 2003). It represents the lecturer's overall emotional response to technology and determines the willingness to adopt and engage with a new system (Dwivedi et al., 2019). Positive attitudes facilitate active engagement and effective utilization, whereas negative attitudes may impede adoption and limit the impact of the technology (Wang et al., 2021). Empirical evidence highlights

the critical role of attitude in shaping lecturers' intentions to adopt AI technologies (Chatterjee & Bhattacharjee, 2020). Based on the previous discussion, we derived the following hypothesis:
H28: Lecturers' attitude positively affects their intention to adopt AIAT.

Behavioural intention to adopt AIAT: refers to a lecturer's intention to use AIAT for assessing students' performance (Venkatesh et al., 2003). It is widely regarded as the earliest indicator of technology adoption (Venkatesh et al., 2003).

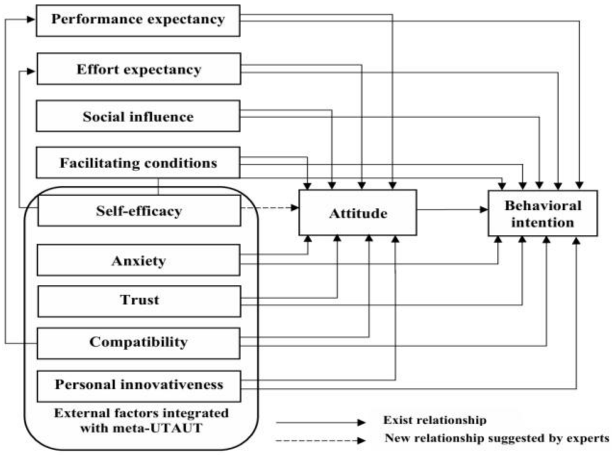

Figure 1. The final proposed model

3. Methodology

A quantitative survey method was used to test the hypotheses, as it effectively captures cause-and-effect relationships. The target population comprises lecturers from 41 universities in the Klang Valley, as they are renowned for their technological advancements in T/L, as reported by the Ministry of Education (2018). This region includes six public universities with 17,277 lecturers and 35 private universities with 7,280 lecturers, totalling 24,557 lecturers, according to the Ministry of Higher Education (2022). Using the online sample size calculator (Raosoft), the minimum required sample size was 379 participants. This sample size is adequate for providing valid results for Structural Equation Modelling (Kline, 2016). Stratified random sampling was used to ensure the accurate representation of the target population. This approach enhances the credibility of the sample by ensuring that all relevant subgroups are adequately represented, particularly in the context of heterogeneous populations with homogeneous subgroups (Taherdoost, 2016). Based on Kothari (2004), the following formula was used to calculate proportional stratified random sampling:

$$The\ sample\ size\ for\ each\ stratum\ = \frac{Stratum\ population}{Total\ population} \times Identified\ sample$$

The sample should include 267 respondents from public universities and 112 from private ones. Simple random sampling was employed to select participants from each stratum using Calculator.net's Random Number Generator.

The instrument was first reviewed for clarity by two IS academics and then validated by 11 experts to ensure content validity, following Lynn's guidance (1986). After two validation rounds, it was refined to 42 items. A pilot study was subsequently conducted to evaluate the instrument's reliability. As noted by Hertzog (2008), an appropriate sample size for pilot studies ranges from 10 to 40 participants per group. Accordingly, 39 responses were collected for the pilot test, comprising 28 participants from public universities and 11 from private universities. The results indicated that all constructs achieved Cronbach's alpha (α) values above the recommended threshold of 0.7, except for one item, which was subsequently removed (Hair et al., 2017). The final instrument and the corresponding internal consistency results are presented in Table 2.

Code	Items	Source	α
Performance expectancy			
PE1	Using the AIAT would enable me to accomplish assessment tasks more quickly.	(Venkatesh et al., 2003)	0.889
PE2	Using the AIAT would enhance my productivity.		
PE3	Using the AIAT would enhance the learning performance of students.		
PE4	Using an AIAT would improve the accuracy of students' assessments.		
PE5	Using the AIAT would help reduce my workload.		
Effort expectancy			
EE1	It would be easy for me to become skilled at using the AIAT.	(Venkatesh et al., 2003)	0.935
EE2	The usage of the AIAT would be easy for me.		
EE3	Learning to use the AIAT would be easy for me.		
EE4	My interaction with the AIAT would be clear and understandable.		
Social influence			
SI1	My colleagues will support the use of the AIAT.	(Venkatesh et al., 2003)	0.972
SI2	My superiors will support the use of the AIAT.		
SI3	The university's top management will support the use of the AIAT.		
Facilitating conditions			
FC1	I have the necessary resources to use the AIAT.	(Venkatesh et al., 2003)	0.789
FC2	I have the necessary knowledge to use the AIAT.		
FC3	The AIAT would be compatible with other technologies or tools I use.		
FC4	I can get assistance from the IT department when I have difficulties using AIAT.		
Self-efficacy			
SE1	I could operate the AIAT correctly even if there is no one around to tell me what to do.	(Venkatesh et al., 2003)	0.918
SE2	I could use the AIAT correctly if I could get assistance when I am stuck.		
SE3	I could learn to use the AIAT correctly if I have a lot of time.		
SE4	I could operate the AIAT correctly if the tool provides the appropriate user guidance and feedback.		
Anxiety			
ANX1	It scares me to think that I could cause the AIAT to destroy a large amount of information by hitting the wrong key.	(Venkatesh et al., 2003)	0.762
ANX2	I hesitate to use the AIAT for fear of making mistakes I cannot correct.		
ANX3	The AIAT is somewhat intimidating to me.		
Trust			
TR1	I trust an AIAT to be reliable.	(Patil et al., 2020)	0.931
TR2	I trust an AIAT to be secure.		
TR3	I believe an AIAT is trustworthy.		
Compatibility			
COM1	Using the AIAT is compatible with all aspects of my work.	(Wang et al., 2020)	0.948
COM2	Using the AIAT is completely compatible with my academic needs.		
COM3	I think that using the AIAT fits with the way I like to assess students' performance.		
COM4	Using the AIAT fits with my educational goals.		
Personal innovativeness			
PI1	If I heard about a new technology like AIAT, I would look for ways to experiment with it.	(Agarwal & Prasad, 1998)	0.939
PI2	Among my peers, I am usually the first to try out a new technology, like AIAT.		
PI3	In general, I am willing to try out a new technology like AIAT.		
PI4	I like to experiment with new technologies like AIAT.		
Attitude			
ATT1	The AIAT is an appropriate tool for lecturers to use.	(Venkatesh et al., 2003)	0.941
ATT2	I like the idea of using the AIAT to assess students' performance.		
ATT3	I think using the AIAT will be advantageous for assessing students' performance.		
ATT4	Overall, my attitude towards using the AIAT is positive.		
Behavioural intention			

BI1	I would like to use the AIAT if I have an opportunity.	(Fan et al., 2018)	0.985
BI2	I would like to use the AIAT as much as possible if I have an opportunity.		
BI3	I make sure I use the AIAT if I have an opportunity.		

Table 2. Construct measurement items and internal consistency reliability results

3.1. Data Collection

The questionnaire, developed using Google Forms, was distributed via email to 379 lecturers across 41 universities in the Klang Valley region. At the initial stage of data collection, the response rate was relatively low (approximately 27.7%), as many lecturers were on extended leave during the holiday season. Accordingly, the number of distributed questionnaires was increased to 758, comprising 534 for public universities and 224 for private universities. This adjustment was made to account for potential nonresponse and unusable data and to ensure that the final dataset was sufficiently robust for meaningful analysis (Pedersen & Nielsen, 2014). Ultimately, 414 of the 758 distributed questionnaires were returned, including 298 from public universities and 116 from private universities. This resulted in an overall response rate of 54.6%, with response rates of 55.9% for public universities and 51.6% for private universities, which are considered acceptable for generating reliable estimates (Sue & Ritter, 2012).

3.2. Data Analysis

Partial Least Squares Structural Equation modelling (PLS-SEM) was used to evaluate the hypotheses using SmartPLS 4. This approach is particularly appropriate when the primary objective is theory development rather than theory confirmation, especially in studies emphasizing prediction and the explanation of key target constructs (Hair et al., 2017).

Before conducting SEM analysis, data preparation and cleaning should be performed. Data cleaning was performed using SPSS 29. No missing data was found; however, 10 responses exhibiting suspicious response patterns (straight-lining) were identified and subsequently removed (Hair et al., 2017), resulting in 404 valid cases. Subsequently, two extreme univariate outliers with highly negative z-scores on performance expectancy (beyond the recommended -4 to $+4$ range) were detected and removed (Tabachnick & Fidell, 2013). In addition, 18 multivariate outliers were identified and removed using Mahalanobis distance at $p < 0.001$. In total, 20 cases were removed, yielding a final dataset of 384 cases for final analysis. Although PLS-SEM is robust to non-normal data, normality assessment was conducted to strengthen the statistical rigour of the study. The results showed that univariate skewness and kurtosis values for all variables were within acceptable thresholds (skewness: -2 to $+2$; kurtosis: -7 to $+7$) (Hair et al., 2017). Furthermore, the Mardia multivariate normality test revealed no significant deviations from normality (Cain et al., 2017), confirming that the dataset met the assumptions of normality. Finally, common method bias was assessed using Harman's single-factor test (1976). The initial component accounted for 39.706% of the total variance, which is below the 50% threshold, indicating that common method variance is unlikely to have significantly influenced the results (Podsakoff & Organ, 1986). SmartPLS 4 was employed to perform the PLS-SEM analysis, as it is widely used and freely available software application for implementing the PLS-SEM technique.

4. Results

4.1. Descriptive Analyses

Descriptive statistics were used to summarize the respondents' demographic characteristics and provide a clear overview of the sample composition. Table 3 explains the characteristics of the respondents.

4.2. Measurement Model Results

Before proceeding to the structural model, the measurement model was rigorously examined to confirm that all latent variables met the required reliability and validity standards. As depicted in Table 4, all factor loadings ranged from 0.515 to 0.956, exceeding the recommended threshold of 0.4; therefore, no items were removed (Hair et al., 2017). In addition, the average variance extracted (AVE) values ranged from 0.6 to 0.906, indicating that each variable accounted for at least 50% of the variance of its indicators and demonstrating adequate convergent validity (Hair et al., 2017). Cronbach's alpha values ranged from 0.781 to 0.948, while composite reliability (CR) values ranged from 0.857 to 0.967, reflecting strong internal consistency and confirming the reliability of the measurement model.

Demographic	Categories	N (384)	%
Age	21-30	13	3.4
	31-40	129	33.6
	41-50	141	36.7
	51-60	79	20.6
	More than 60	22	5.7
Gender	Male	140	36.5
	Female	244	63.5
Academic qualification	Bachelor's degree	6	1.6
	Master's degree	127	33.1
	PhD	251	65.3
Type of university	Public university	272	70.8
	Private university	112	29.2
Faculty	Computer science	33	8.6
	Social science	46	12.0
	Education	39	10.2
	Business	70	18.2
	Engineering	36	9.4
	Medicine	37	9.6
	Others	123	32.0
Academic position	Assistant Lecturer\Tutor\Instructor	11	2.9
	Lecturer	99	25.8
	Senior Lecturer\Assistant Professor	164	42.7
	Associate Professor	69	18.0
	Professor	37	9.6
	Others	4	1.0
Tenure of teaching (years)	Less than 3	42	10.9
	4-7	65	16.9
	8-11	63	16.4
	12-15	66	17.2
	More than15	148	38.5
General knowledge of AI	Terrible	14	3.7
	Poor	41	10.7
	Average	187	49.0
	Good	122	31.9
	Excellent	18	4.7
AI-enabled services or tools have been used for educational purposes	None	9	2.4
	Turnitin	341	90.7
	Grammarly	261	69.4
	QuillBot	153	40.7
	ChatGPT	122	32.4
	Scholarly	70	18.6
	Semantic Scholar	57	15.2
	Trinka	4	1.1
	Elicit	3	0.8
	Connected Papers	37	9.8
	Others	18	4.8

Table 3. Demographic information of respondents

Variable	Items	Factor loadings	Average variance extracted	Cronbach's alpha (α)	Composite reliability
Anxiety	ANX1	0.799	0.756	0.852	0.903
	ANX2	0.886			
	ANX3	0.920			
Attitude	ATT1	0.883	0.833	0.933	0.952
	ATT2	0.935			
	ATT3	0.925			
	ATT4	0.907			
Behavioural intention	BI1	0.948	0.906	0.948	0.967
	BI2	0.956			
	BI3	0.951			
Compatibility	COM1	0.869	0.805	0.919	0.943
	COM2	0.891			
	COM3	0.924			
	COM4	0.904			
Effort expectancy	EE1	0.878	0.805	0.919	0.943
	EE2	0.913			
	EE3	0.916			
	EE4	0.881			
Facilitating conditions	FC1	0.852	0.625	0.793	0.866
	FC2	0.864			
	FC3	0.875			
	FC4	0.515			
Performance expectancy	PE1	0.856	0.620	0.845	0.890
	PE2	0.867			
	PE3	0.729			
	PE4	0.728			
	PE5	0.747			
Personal innovativeness	PI1	0.886	0.771	0.901	0.931
	PI2	0.807			
	PI3	0.881			
	PI4	0.934			
Self-efficacy	SE1	0.749	0.600	0.781	0.857
	SE2	0.818			
	SE3	0.724			
	SE4	0.803			
Social influence	SI1	0.889	0.787	0.865	0.917
	SI2	0.921			
	SI3	0.850			
Trust	TR1	0.909	0.811	0.883	0.928
	TR2	0.895			
	TR3	0.897			

Table 4. Convergent validity and composite reliability of the variables

Discriminant validity was assessed using two widely recognized methods: Fornell and Larcker (1981) criterion and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015), as presented in Table 5. According to Fornell and Larcker (1981), discriminant validity is confirmed when the square root of a variable's AVE exceeds its correlations with other variables. The results show that all variables in the measurement model satisfy this criterion, consistent with Chin (1998). Additionally, all HTMT values were below the 0.90 threshold, indicating clear distinctions among the variables and confirming adequate discriminant validity (Hair et al., 2017).

	Variable	ANX	ATT	BI	COM	EE	FC	PE	PI	SE	SI	TR
Fornell–Larcker criterion	ANX	0.873										
	ATT	-0.189	0.923									
	BI	-0.203	0.829	0.957								
	COM	-0.198	0.764	0.679	0.906							
	EE	-0.256	0.6	0.573	0.528	0.897						
	FC	-0.153	0.444	0.393	0.462	0.632	0.794					
	PE	-0.094	0.695	0.669	0.666	0.57	0.456	0.803				
	PI	-0.255	0.652	0.719	0.562	0.59	0.408	0.517	0.88			
	SE	-0.163	0.526	0.572	0.448	0.595	0.537	0.493	0.514	0.793		
	SI	0.042	0.368	0.328	0.384	0.318	0.494	0.458	0.217	0.394	0.889	
	TR	-0.059	0.617	0.546	0.693	0.418	0.372	0.587	0.423	0.374	0.347	0.914
Heterotrait-Monotrait (HTMT) ratio	ANX											
	ATT	0.211										
	BI	0.217	0.850									
	COM	0.229	0.801	0.687								
	EE	0.275	0.632	0.587	0.559							
	FC	0.180	0.502	0.421	0.539	0.712						
	PE	0.145	0.732	0.676	0.695	0.641	0.549					
	PI	0.273	0.683	0.759	0.587	0.631	0.454	0.544				
	SE	0.215	0.595	0.639	0.486	0.672	0.614	0.555	0.600			
	SI	0.069	0.367	0.308	0.384	0.337	0.633	0.488	0.196	0.456		
	TR	0.097	0.651	0.539	0.725	0.457	0.458	0.627	0.438	0.397	0.331	
Notes: PE: Performance expectancy, EE: Effort expectancy, SI: Social influence, FC: Facilitating conditions, SE: Self-efficacy, ANX: Anxiety, TR: Trust, COM: Compatibility, PI: Personal innovativeness, ATT: Attitude towards AIAT, BI: Behavioural intention to adopt AIAT												

Table 5. Discriminant validity assessment

4.2.1. Structural Model Results

The analysis revealed that BI was positively influenced by PE, SE, PI, and ATT, with ATT exerting the strongest effect. Accordingly, H2, H14, H26, and H28 were supported, as summarized in Table 6. FC exhibited a statistically significant but weak negative effect on BI, thereby rejecting H11. The effects of EE, SI, ANX, TR, and COM on BI were non-significant, thereby rejecting H5, H8, H17, H20, and H23.

In contrast, ATT was positively influenced by PE, EE, SE, TR, COM, and PI, with COM having the strongest effect, supporting H1, H4, H13, H19, H22, and H25. Whereas SI, FC, and ANX had an insignificant impact, rejecting H7, H10, and H16. COM positively influenced PE, and SE positively influenced EE, thereby supporting H23a and H14a, respectively.

Additionally, the results demonstrate that ATT partially mediates the relationships between PE, SE, PI, and BI, supporting H3, H15, and H27. Moreover, ATT fully mediates the relationships between EE, TR, COM, and BI, supporting H6, H21, and H24. In contrast, ATT did not exert a significant mediating effect on the relationships between SI, FC, ANX, and BI, thereby rejecting H9, H12, and H18.

Hypotheses		Direct effects			Indirect effects			Decision
		β	T-value	P-value	β	T-value	P-value	
H1	PE → ATT	0.177	3.859	0.000***				Supported
H2	PE → BI	0.107	2.327	0.020*				Supported
H3	PE → ATT → BI				0.087	3.518	0.000***	Supported
H4	EE → ATT	0.097	2.237	0.025*				Supported
H5	EE → BI	-0.022	0.555	0.579				Rejected
H6	EE → ATT → BI				0.048	2.149	0.016*	Supported
H7	SI → ATT	0.022	0.655	0.513				Rejected
H8	SI→ BI	0.005	0.159	0.874				Rejected
H9	SI → ATT → BI				0.011	0.649	0.258	Rejected
H10	FC → ATT	-0.057	1.423	0.155				Rejected

H11	FC → BI	-0.086	2.262	0.024*				Rejected
H12	FC → ATT → BI				-0.028	1.407	0.080	Rejected
H13	SE → ATT	0.087	2.097	0.036*				Supported
H14	SE → BI	0.137	3.852	0.000***				Supported
H14a	SE → EE	0.600	17.090	0.000***				Supported
H15	SE → ATT → BI				0.043	2.089	0.018*	Supported
H16	ANX → ATT	-0.008	0.251	0.802				Rejected
H17	ANX → BI	-0.009	0.346	0.729				Rejected
H18	ANX → ATT → BI				-0.004	0.250	0.401	Rejected
H19	TR → ATT	0.109	2.201	0.028*				Supported
H20	TR→ BI	-0.008	0.208	0.835				Rejected
H21	TR → ATT → BI				0.054	2.214	0.013*	Supported
H22	COM → ATT	0.377	6.992	0.000***				Supported
H23	COM → BI	0.046	1.044	0.296				Rejected
H23a	COM → PE	0.612	15.637	0.000***				Supported
H24	COM → ATT → BI				0.186	5.616	0.000***	Supported
H25	PI → ATT	0.218	4.650	0.000***				Supported
H26	PI → BI	0.295	6.273	0.000***				Supported
H27	PI → ATT → BI				0.108	3.923	0.000***	Supported
H28	ATT → BI	0.493	9.310	0.000***				Supported
Notes: *** $p < 0.001$, * $p < 0.05$. PE: Performance expectancy, EE: Effort expectancy, SI: Social influence, FC: Facilitating conditions, SE: Self-efficacy, ANX: Anxiety, TR: Trust, COM: Compatibility, PI: Personal innovativeness, ATT: Attitude towards AIAT, BI: Behavioural intention to adopt AIAT								

Table 6. Hypothesis testing results

Table 7 indicates that the model accounts for a significant proportion of variance in both ATT and BI ($R^2 > 0.67$), affirming the statistical significance and theoretical robustness of the model (Cohen, 1988). The R^2 values for EE and PE reflected moderate explanatory power ($R^2 > 0.33$) (Hair et al., 2017).

Variable	R^2	Q^2 predict
Attitude towards adopting AI-based assessment tools	0.683	0.639
Intention to adopt AI-based assessment tools	0.728	0.612
Effort expectancy	0.360	0.354
Performance expectancy	0.375	0.371

Table 7. Coefficient of determination values (R^2) and relevance predictive (Q^2) for the model

The effect sizes range from 0.000 (negligible) to 0.600 (large), revealing substantial variation in the influence of the predictors, as shown in Table 8. COM is the strongest determinant of ATT, exhibiting a medium effect ($f^2 \geq 0.15$) (Hair et al., 2017), underscoring its central role in shaping it. This is followed by PI and PE, each of which demonstrated a small effect ($f^2 \geq 0.02$) (Hair et al., 2017). The remaining variables showed negligible influence. Regarding lecturers' intention, ATT exerted the strongest influence with a medium effect, followed by PI, which also exhibited a medium effect, revealing their central role in shaping BI. SE and PE showed small effects, whereas the others contributed negligibly to BI. Finally, the effects of COM on PE and SE on EE were both large ($f^2 \geq 0.35$).

Variable	Endogenous variable			
	Attitude	Behavioural intention	Effort expectancy	Performance expectancy
Anxiety	0.000	0.000		
Attitude		0.283		
Compatibility	0.185	0.003		0.600
Effort expectancy	0.012	0.001		
Facilitating conditions	0.005	0.013		
Performance expectancy	0.047	0.019		

Personal innovativeness	0.082	0.161		
Self-efficacy	0.013	0.037	0.562	
Social influence	0.001	0.000		
Trust	0.020	0.000		

Table 8. Effect size (f^2) for the endogenous variables

The model's ability to predict new observations was evaluated and found to be strong. Table 7 revealed that ATT and BI have high predictive relevance ($Q^2 \geq 0.50$), whereas EE and PE exhibited moderate predictive relevance ($Q^2 \geq 0.25$) (Hair et al., 2017). To provide additional insights into the quality of PLS-SEM path model estimates, the q^2 effect size was assessed. Table 9 indicate that most of the predictive relevance effect sizes were below the 0.02 threshold, implying no meaningful predictive effect (Hair et al., 2017). This is likely attributable to multiple predictors that did not exhibit significant effects, while for BI, only COM, TR, and PI yielded small effects, indicating modest predictive relevance overall.

Exogenous variable	Endogenous variable	Q^2 included	Q^2 excluded	Effect size (q^2)	Result
Anxiety	Attitude towards adopting AI-based assessment tools	0.639	0.641	-0.006	No effect
Compatibility			0.603	0.100	Small
Effort expectancy			0.641	-0.006	No effect
Facilitating conditions			0.642	-0.008	No effect
Performance expectancy			0.64	-0.003	No effect
Personal innovativeness			0.597	0.116	Small
Self-efficacy			0.638	0.003	No effect
Social influence			0.64	-0.003	No effect
Trust			0.629	0.028	Small
Anxiety	Intention to adopt AI-based assessment tools	0.612	0.614	-0.005	No effect
Attitude			0.612	0.000	No effect
Compatibility			0.615	-0.008	No effect
Effort expectancy			0.612	0.000	No effect
Facilitating conditions			0.611	0.003	No effect
Performance expectancy			0.615	-0.008	No effect
Personal innovativeness			0.556	0.144	Small
Self-efficacy			0.603	0.023	Small
Social influence			0.613	-0.003	No effect
Trust			0.614	-0.005	No effect
Self-efficacy	Effort expectancy	0.354			Large
Compatibility	Performance expectancy	0.371			Large

Table 9. Effect size (q^2) for the endogenous variables

5. Discussion

This research employed the extended meta-UTAUT model as the theoretical framework to investigate Malaysian lecturers' attitudes and intentions to adopt AIAT in universities. The results show that 18 hypotheses were supported, including 12 direct relationships and six indirect relationships mediated by ATT, while 12 hypotheses were not supported, comprising nine direct relationships and three mediated relationships. These findings indicate that the meta-UTAUT model was partially supported. ATT mediated the effects of certain independent factors on BI but did not mediate others, suggesting that the mediating role of ATT is context-dependent and construct-specific rather than universal. This highlights limitations in the meta-UTAUT assumption that ATT consistently bridges all antecedents and BI.

PE is a key predictor of both ATT and BI. Lecturers are more likely to develop favourable attitudes and stronger intentions to adopt AIAT when they perceive these technologies as capable of accelerating the assessment process, increasing their productivity, enhancing student learning outcomes, improving grading accuracy, and reducing workload, as reflected in the measurement items. They tend to value technologies that enhance teaching effectiveness and assessment quality (González-Calatayud et al., 2021), which in turn motivates their adoption of AIAT rather than reliance on colleagues' opinions or institutional mandates (Nadzirah Muhammad et al., 2025). Previous studies in HE consistently identify PE as a critical determinant of technology adoption among lecturers, either by shaping ATT (Helmiatin et al., 2024), directly influencing BI (Strzelecki et al., 2024), or indirectly affecting intention through the mediating role of ATT (Prakash & Das, 2021). Consistent with these findings, lecturers' positive attitudes reinforce their intention to adopt AIAT, highlighting ATT as a key psychological mechanism through which performance-related beliefs translate into BI. These findings are theoretically supported by the Decomposed Theory of Planned Behaviour (DTPB) (Taylor & Todd, 1995), UTAUT and its extensions (UTAUT2, UTAUT3, meta-UTAUT), and TAM and its extensions (TAM2 and TAM3), which emphasise PE as a driver of ATT and/or BI. However, unlike UTAUT, PE was not the strongest direct predictor of BI in this study. This may be attributed to the novelty of AIAT, as lecturers remain cautious due to limited experience and uncertainty regarding reliability and integration. Similar patterns have been observed in studies of other emerging educational technologies (Elatrachi & Oukarfi, 2020).

EE significantly influenced lecturers' ATT toward AIAT, indicating that when lecturers perceive AIAT as easy to learn and use, requiring minimal effort (i.e., based on the items), they are more likely to develop positive attitudes toward them. This finding aligns with prior studies (Helmiatin et al., 2024) and with the meta-UTAUT, TAM, and DTPB models. However, the modest effect suggests that although lecturers value ease of use, it mainly reduces perceived barriers to adoption rather than acting as a strong motivational driver shaping attitudes. This relatively weak influence may be attributed to Malaysian lecturers' baseline digital competence and their prior exposure to learning management systems, online assessment platforms, and other educational technologies, which reduces sensitivity to usability concerns (Mansour & Mansour, 2025). Consequently, further reductions in perceived effort contribute only marginally to attitude formation. The non-significant direct effect of EE on BI further supports this interpretation. Lecturers may be willing to invest effort in using AIAT when clear benefits are expected (Strzelecki et al., 2024), reflecting a shift from effort avoidance to outcome maximization, where perceived usefulness outweighs usability concerns (Wang et al., 2021). As a result, the influence of EE diminishes when tangible performance gains are anticipated (Zaim et al., 2024). Although this finding contrasts with the direct-effect assumptions of UTAUT and TAM, the significant indirect effect through ATT supports the meta-UTAUT perspective. EE shapes positive attitudes toward AIAT, which in turn increases adoption intention, consistent with prior research (Wang et al., 2021). In this context, ATT functions as a mediating mechanism that translates EE perceptions into BI. However, the modest mediation effect suggests that simplifying AIAT alone is unlikely to substantially increase adoption without clear performance benefits (Wang et al., 2021).

Meanwhile, SI was not a significant predictor in this context, showing no effect on ATT or BI, either directly or indirectly through ATT. This suggests that lecturers' attitudes and intentions are largely unaffected by the views of colleagues, superiors, or top management (i.e., based on the items). These findings align with prior studies on AI adoption among academics (Baig & Yadegaridehkordi, 2025; Bervell et al., 2020; Enang & Christopoulou, 2025). However, they diverge from the meta-UTAUT model, indicating that the salience of this construct is highly context dependent. In Malaysian higher education institutions (MHEI), AIAT adoption remains at an early stage with limited uptake (AIBIG, 2024), reflecting a voluntary environment driven primarily by individual initiative rather than institutional mandates (Mohamad Mozie et al., 2025). Consequently, the effect of SI may be diminished in early-stage adoption contexts, where lecturers with limited experience encounter minimal peer or managerial pressure (Venkatesh et al., 2003).

FC did not significantly influence lecturers' attitudes toward AIAT. In MHEI, this can be attributed to structural and cultural factors. Malaysian universities have invested extensively in digital infrastructure, learning management systems, and institutional initiatives aligned with national digitalization agendas, such as the Malaysia Digital Economy Blueprint (Mohamad Mozie et al., 2025). Consequently, facilitating conditions, such as access to systems and technical support, are increasingly perceived as standard or taken-for-granted, rather than as factors shaping positive attitudes (Bahari et al., 2023). Similar findings have been reported in Malaysian universities' technology adoption studies (Bahari et al., 2023; Chun & Yunus, 2023). Interestingly, FC exhibited a significant but small negative direct effect on AIAT adoption intention, consistent with prior studies (Zaim et al., 2024). This contrasts with Perez (2024), who found that adoption is more likely when institutional support and resources are adequate, and users are confident and knowledgeable. In the present context, limited AIAT knowledge and experience among lecturers may heighten perceptions of complexity, risk, or misalignment with pedagogical practices, thereby reducing their willingness to adopt these tools (Adirinekso et al., 2020). The indirect effect of FC on BI through ATT was non-significant, confirming that ATT does not mediate this relationship. Lecturers tend to prioritise cognitive and performance-oriented evaluations over contextual enablers, weakening the effect of FC. This pattern is consistent with evidence from Asian higher education settings where FC fail to translate into intention through

ATT (Kwak, Seo, et al., 2022). These results challenge the meta-UTAUT assumption that FC universally enable technology adoption.

SE influenced lecturers' attitudes, with higher SE fostering more positive attitudes, consistent with Wang et al. (2021). In MHEI, lecturers often demonstrate high SE due to regular engagement with digital systems integral to teaching, such as learning management systems. This experience builds competence, confidence, and familiarity with digital tools, reinforcing their belief in their ability to learn and use new technologies effectively (Teo, 2018). However, the relatively small effect of SE on ATT suggests that other factors, such as PE and PI, play a more prominent role in shaping ATT. Similarly, the significant direct effect of SE on BI indicates that enhancing lecturers' competence and confidence is a key mechanism for promoting AIAT adoption, consistent with prior studies (Herodotou et al., 2023). Lecturers are more likely to engage with AIAT when they feel capable of using the tools independently, can access support as needed, have sufficient time to learn, and receive clear guidance and feedback (i.e., based on the items). The mediated effect through ATT further emphasizes that attitudinal mechanisms transmit the influence of SE to adoption intentions, as supported by Wang et al. (2021). This indicates that confidence not only directly drives intention but also reinforces positive perceptions, increasing the likelihood of engagement with AIAT. This pattern underscores the central role of ATT as a bridge between perceptions and BI, consistent with the meta-UTAUT model, which emphasizes that users' beliefs and perceptions are translated into intention primarily through their attitudinal response. Additionally, SE strongly shapes EE, aligning with TAM3 and prior research (Wang et al., 2021). Lecturers with higher confidence are more likely to perceive new tools as manageable, reducing anxiety and perceived complexity even before actual interaction (Teo, 2018).

ANX was not a barrier in this study, as it did not significantly predict ATT or BI, either directly or indirectly, consistent with previous research (Wang et al., 2021). This suggests that Malaysian lecturers' technology-related apprehension has largely diminished due to their accumulated experience with educational information systems, including AI-related tools, which reduces uncertainty and perceived risk associated with AIAT use (Henderson & Corry, 2021). High levels of SE further enable lecturers to perceive AIAT as controllable and manageable, shifting evaluations from emotional concerns to task- and performance-oriented considerations (Kai et al., 2026). Consequently, the absence of a significant anxiety effect reflects a context in which experience, confidence, and rational evaluation have largely supplanted anxiety as determinants of AIAT adoption. Within TAM and UTAUT frameworks, ANX is often considered a peripheral factor whose influence diminishes as users gain experience and familiarity, explaining its non-significant role in more digitally mature environments (Venkatesh et al., 2003).

TR significantly influenced ATT, consistent with prior findings (Xiong et al., 2023). When lecturers perceive AIAT as reliable, secure, and trustworthy (i.e., based on the items), they are more likely to develop a positive attitude toward integrating these tools into teaching and assessment. In MHEI, where assessment integrity and accountability are critical, TR reduces perceived uncertainty and professional risk, allowing lecturers to view AIAT as legitimate and pedagogically appropriate. Thus, TR primarily operates at the attitudinal level, shaping lecturers' cognitive and emotional evaluations. In contrast, the non-significant direct effect of TR on BI suggests that TR is insufficient to drive adoption decisions, consistent with prior research (Chuyen, 2023). Trust in AI depends on perceptions of system capability, reliability, security, and ethical use, which are critical considerations for all stakeholders in the educational ecosystem (Salloum, 2024). Lecturers often require clear evidence of AI systems' effectiveness before developing confidence in their use (Bhat et al., 2024), as AI-generated outputs may still be inaccurate or misaligned with factual information (U.S. Department of Education, 2023). Furthermore, the use of AI in T/L introduces potential safety and privacy risks, particularly regarding student data, which may be vulnerable to cyberattacks or data breaches, thereby undermining trust (Dhawan & Batra, 2020). Familiarity and prior experience are key antecedents of trust, as repeated interaction enables users to form expectations, reduce uncertainty, and evaluate system attributes such as reliability and competence (Teo, 2018). In the context of MHEI, lecturers have limited hands-on experience and knowledge with AIAT, making it more difficult to assess these tools and potentially amplifying perceived risks and uncertainty, thereby weakening trust and limiting its direct influence on adoption intentions (Kuen et al., 2023). Whereas TR indirectly affected BI through ATT, consistent with prior findings (Roh et al., 2023). Lecturers who trust AIAT are more likely to develop positive attitudes toward their use, which subsequently strengthens their adoption intentions. Thus, TR enhances intention primarily when it fosters a favourable evaluative response rather than acting as an independent driver. This is consistent with the meta-UTAUT model, where ATT functions as a critical intermediary that translates trust perceptions into BI. However, the small effect size suggests limited practical significance in this context (Hair et al., 2017).

COM had the strongest effect on ATT, supporting the DTPB model and prior findings (Nuha et al., 2018). Compatibility reduces disruption and makes technology use feel natural when it aligns with lecturers' work tasks, academic needs, assessment practices, and pedagogical goals (i.e., based on the items) rather than being burdensome (Gupta & Bhaskar, 2020). This alignment lowers cognitive load and reduces resistance, explaining its strong positive effect on ATT (Gunnoo et al., 2023). However, COM did not directly predict BI, consistent with prior research (Yedilbayev et al., 2023). In the MHEI context, AIAT remains at an early stage, with lecturers largely overlooking these tools, resulting in limited knowledge and experience (AIBIG, 2024). Experience shapes how users perceive fit and task alignment; without familiarity or hands-on exposure, compatibility may have little effect on intention, as users struggle to evaluate how a technology integrates into their routines (Rahman et al., 2019). Consequently, lecturers may find it difficult to assess AIAT effectively, leaving many uncertain about adoption due to their limited exposure and incomplete understanding of the technology. COM exerted a significant indirect effect on BI through ATT, consistent with prior findings (Gunnoo et al., 2023). This indicates that COM primarily influences adoption via the attitudinal pathway rather than directly, particularly when users are unfamiliar with the technology. The indirect effect underscores ATT's critical role as a mediator in the adoption decision-making process, in line with the meta-UTAUT framework. Moreover, COM is a strong predictor of PE, in line with previous research (Oluyinka et al., 2021). This suggests that when lecturers perceive AIAT as aligned with their teaching and assessment practices, they are more likely to view the tools as effective for enhancing the assessment process.

PI was a key determinant of both ATT and BI, directly and indirectly through ATT, consistent with prior research (Patil et al., 2020; Strzelecki et al., 2024). In MHEIs, where AIAT remains unfamiliar and lecturers have limited knowledge and experience, PI becomes particularly important. Lecturers with high PI are more likely to experiment with AIAT, evaluate its relevance, and learn its features, thereby compensating for limited institutional guidance and fostering more positive attitudes and stronger adoption intentions (Farooq et al., 2017). Consequently, PI acts as a self-driven catalyst that enables early adopters to overcome uncertainty and barriers associated with emerging technologies (Ciftci et al., 2021). The significant indirect effect through ATT further highlights its role in shaping adoption decisions, with attitude functioning as a conduit between PI and BI, consistent with the meta-UTAUT model.

Finally, ATT emerged as the strongest predictor of lecturers' intention to adopt AIAT. This finding is consistent with TAM, TRA, TPB, DTPB, meta-UTAUT, as well as previous studies (Wang et al., 2021). Lecturers are more likely to adopt AIAT when they perceive these technologies as suitable tools for student assessment, recognize their advantages in evaluating student performance, and hold positive attitudes toward their use, as reflected in the measured items, which ultimately translate into strong adoption intentions.

6. Theoretical Contributions

This study extends the literature on technology adoption in HE by applying the meta-UTAUT model in the context of AIAT. The empirical analysis reveals partial support for the meta-UTAUT model and highlights the role of attitude in shaping behavioural intention. Additionally, this study develops and tests a conceptual model that incorporates several factors associated with lecturers' adoption of AIAT, some of which have not been examined in this context. In contrast to many prior studies that treat attitude as the final dependent variable, this study examines lecturers' behavioural intention as the outcome variable. Moreover, the independent variables are specified as antecedents of both attitude and behavioural intention, allowing the relationships among these variables to be examined simultaneously. The analysis further evaluates the mediating role of attitude within the meta-UTAUT framework, providing additional empirical evidence on the relationships among these variables. By examining these factors and their relationships, the study contributes to the limited literature on AIAT adoption and enhances understanding of the adoption of AI-based educational systems in HE.

7. Practical Contributions

To promote AIAT adoption in HE, policymakers and institutional leaders should implement a comprehensive support strategy. First, targeted workshops can enhance lecturers' understanding of AIAT features and functionalities by emphasizing practical benefits and alignment with pedagogical objectives, assessment practices, and existing workflows to strengthen perceived usefulness. Second, structured training programs, detailed user documentation, and dedicated technical support should be provided to boost lecturers' technical competence, confidence, and perceived ease of use. Third, trust-building measures are essential; these include initiatives to ensure system reliability, implementation of certified security frameworks, and establishment of clear policies for ethical and responsible AI use to mitigate associated risks. Fourth, early adopters should be identified through pilot implementations involving diverse lecturers and positioned as opinion leaders to facilitate broader acceptance.

Additionally, developers and designers must ensure that AIAT delivers accurate, pedagogically aligned assessments and maintains high usability standards; involving lecturers in the design and development process is critical to align the tools with instructional needs. Taken together, these coordinated efforts can foster positive attitudes towards AIAT and behavioural intention, supporting its effective integration into higher education practices.

8. Limitations and Future Research

This study has several limitations. First, the limited availability of empirical research on AIAT adoption in higher education constrains the opportunity to compare and contextualize the results. Second, although the sample of 414 participants was sufficient for statistical analysis, a larger sample would likely provide more nuanced insights, particularly if it included more lecturers from private universities. Third, data were collected at a single point in time, resulting in a cross-sectional rather than longitudinal design. Longitudinal design is generally more effective for examining causal relationships and capturing changes over time; however, the cross-sectional design effectively addressed the research objectives.

Future research could extend the model by incorporating additional AI-related factors, such as system likability, perceived intelligence, and anthropomorphism, to provide a more comprehensive understanding of adoption behavior. Moreover, expanding the sample to include lecturers from all Malaysian universities would enhance the generalizability of the findings. Targeted sampling across different institutional types could also support comparative analyses between public and private universities, revealing potential contextual differences in adoption patterns. Finally, this study examined behavioral intention rather than actual usage. Therefore, future studies should investigate actual usage behavior, as behavioral intention does not always translate into practice.

9. Conclusions

This research examines lecturers' attitudes and behavioural intentions toward adopting AIAT in Malaysian universities. A meta-UTAUT-based model incorporating external factors was proposed and empirically tested using survey data collected from 414 lecturers in the Klang Valley. The findings indicate that performance expectancy, effort expectancy, self-efficacy, trust, compatibility, and personal innovativeness significantly shape lecturers' attitudes towards AIAT. Moreover, performance expectancy, self-efficacy, personal innovativeness, and attitude are key determinants of adoption intention. The results further demonstrate that attitude mediates the relationship between performance expectancy, effort expectancy, self-efficacy, trust, compatibility, personal innovativeness, and the intention to adopt AIAT. These findings would provide practical guidance for fostering the effective adoption and integration of AI technologies in Malaysian higher education institutions.

References

Adirinekso, G. P., Purba, J. T., & Budiono, S. (2020). Measurement of performance, effort, social influence, facilitation, habit and hedonic motives toward pay later application intention: Indonesia evidence. In the Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management, Harare, Zimbabwe.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 204-215.

AIBIG. (2024). *AI spectrum bulletin: AI ethics: Balancing innovation and responsibility* (3009-1950). (AI Spectrum Bulletin Series, Issue. U. M. Kelantan. https://aibig.umk.edu.my/img/buletin/AI%20Spectrum%20Edition%202.pdf

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211. https://doi.org/https://doi.org/10.1016/0749-5978(91)90020-T

Akil, W. F. H. W. M., & Matore, M. E. E. M. (2023). The 21st century assessment strategies in medical laboratory education: sharing experiences between two higher institutions in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, *13*(7), 107-130. https://doi.org/http://dx.doi.org/10.6007/IJARBSS/v13-i7/17196

Alfaleh, M. (2026). Sustainable AI-driven assessment in higher education: A systematic review of fairness, transparency, pedagogical innovation, and governance. *Sustainability*, *18*(2), 785. https://www.mdpi.com/2071-1050/18/2/785

Ali, Q. I. (2024). Towards more effective summative assessment in OBE: A new framework integrating direct measurements and technology. *Discover Education*, *3*(1), 107. https://doi.org/https://doi.org/10.1007/s44217-024-00208-5

Alkhowaiter, W. A. (2022). Use and behavioural intention of m-payment in GCC countries: Extending meta-UTAUT with trust and Islamic religiosity. *Journal of Innovation and Knowledge, 7*(4), 100240. https://doi.org/https://doi.org/10.1016/j.jik.2022.100240

Altalhi, M. (2021). Toward a model for acceptance of MOOCs in higher education: The modified UTAUT model for Saudi Arabia. *Education and Information Technologies*, *26*(2), 1589-1605. https://doi.org/https://doi.org/10.1007/s10639-020-10317-x

Bahari, M., Arpaci, I., Azmi, N. F. M., & Shuib, L. (2023). Predicting the intention to use learning analytics for academic advising in higher education. *Sustainability*, *15*(21), 15190. https://doi.org/https://doi.org/10.3390/su152115190

Baig, M. I., & Yadegaridehkordi, E. (2025). Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education. *International Journal of Educational Technology in Higher Education*, *22*(5). https://doi.org/https://doi.org/10.1186/s41239-025-00506-4

Baker, T., Smith, L., & Anissa, N. (2019). *Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges*. Nesta. https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, *180*, 121692. https://doi.org/https://doi.org/10.1016/j.techfore.2022.121692

Bellet, T., & Banet, A. (2023). UTAUT4-AV: An extension of the UTAUT model to study intention to use automated shuttles and the societal acceptance of different types of automated vehicles. *Transportation research part F: traffic psychology and behaviour*, *99*, 239-261. https://doi.org/https://doi.org/10.1016/j.trf.2023.10.007

Bervell, B., Nyagorme, P., & Arkorful, V. (2020). LMS-enabled blended learning use intentions among distance education tutors: Examining the mediation role of attitude based on technology-related stimulus-response theoretical framework. *Contemporary Educational Technology*, *12*(2), ep273. https://doi.org/https://doi.org/10.30935/cedtech/8317

Bhat, M. A., Tiwari, C. K., Bhaskar, P., & Khan, S. T. (2024). Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. *Journal of Information, Communication and Ethics in Society*, *22*(3), 331-353. https://doi.org/https://doi.org/10.1108/JICES-03-2024-0033

Bhattacherjee, A. (2012). *Social Science Research: Principles, Methods, and Practices* (2nd ed.). University of South Florida. https://digitalcommons.usf.edu/oa_textbooks/3

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education 21*(4). https://doi.org/https://doi.org/10.1186/s41239-023-00436-z

Braga, P. R. V., Granero, C. M. O., & Buck, E. (2024). Student and faculty perceptions of summative assessment methods in a block and blend mode of delivery. *Journal of University Teaching and Learning Practice*, *21*(2). https://doi.org/https://doi.org/10.53761/1.21.2.04

Cain, M. K., Zhang, Z., & Yuan, K.-H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*, *49*(5), 1716-1735. https://doi.org/https://doi.org/10.3758/s13428-016-0814-1

Camacho-Miñano, M.-d.-M., del Campo, C., Urquía-Grande, E., Pascual-Ezama, D., Akpinar, M., & Rivero, C. (2020). Solving the mystery about the factors conditioning higher education students' assessment: Finland versus Spain. *Education + Training*, *62*(6), 617-630. https://doi.org/https://doi.org/10.1108/ET-08-2019-0168

Chassab, R. H., Zakaria, L. Q., & Tiun, S. (2021). Automatic essay scoring: A review on the feature analysis techniques. *International Journal of Advanced Computer Science and Applications*, *12*(10), 252-264. https://doi.org/ http://dx.doi.org/10.14569/IJACSA.2021.0121028

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443-3463. https://doi.org/https://doi.org/10.1007/s10639-020-10159-7

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing organizational users' intentions and behavior to AI integrated CRM systems: A Meta-UTAUT approach. *Information Systems Frontiers*, *25*(4), 1299-1313. https://doi.org/https://doi.org/10.1007/s10796-021-10181-1

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Psychology Press.

Chun, T. W., & Yunus, M. M. (2023). Factors affecting Malaysian ESL teachers' behavioral intentions for technology use in the post-COVID-19 era [Brief Research Report]. *Frontiers in psychology*, *Volume 14 - 2023*. https://doi.org/10.3389/fpsyg.2023.1127272

Chuyen, N. T. H. (2023). An empirical analysis of predictors of AI-powered design tool adoption. *TEM Journal*, *12*(3), 1482-1489. https://doi.org/https://doi.org/10.18421/TEM123-28

Ciftci, O., Berezina, K., & Kang, M. (2021). Effect of personal innovativeness on technology adoption in hospitality and tourism: Meta-analysis. In W. Wörndl, C. Koo, & J. L. Stienmetz, *Information and Communication Technologies in Tourism 2021* Cham.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/https://doi.org/10.4324/9780203771587

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, *23*(2), 145-158. https://doi.org/10.2307/249749

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189-211. https://doi.org/https://doi.org/10.2307/249688

Daniel Mehari Alemayehu, D. N. K. D. (2023). Evolution of technology adoption theories and models: A review of literature. *European Economic Letters (EEL)*, *13*(5), 1472-1486. https://www.eelet.org.uk/index.php/journal/article/view/932

Deep, P. D., Edgington, W. D., Ghosh, N., & Rahaman, M. S. (2025). Evaluating the effectiveness and ethical implications of AI detection tools in higher education. *Information*, *16*(10), 905. https://www.mdpi.com/2078-2489/16/10/905

Dhawan, S., & Batra, G. (2020). Artificial intelligence in higher education: Promises, perils, and perspective. *OJAS Expanding Knowledge Horizon*, *9*(2), 11-22.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719-734. https://doi.org/https://doi.org/10.1007/s10796-017-9774-y

Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): A review of emerging literature. *Current Opinion in Psychology*, *36*, 13-18. https://doi.org/https://doi.org/10.1016/j.copsyc.2020.03.008

Elatrachi, M., & Oukarfi, S. (2020). Determinants of ICT integration by teachers in higher education in Morocco. In A. Kavoura, E. Kefallonitis, & P. Theodoridis, *Strategic Innovative Marketing and Tourism* Cham.

Enang, E., & Christopoulou, D. (2025). Exploring academic's intentions to incorporate ChatGPT into their teaching practice. *Journal of University Teaching and Learning Practice*, *21*(08). https://doi.org/https://doi.org/10.53761/rn5y5614

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2018). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research*, *294*(1), 567-592. https://doi.org/https://doi.org/10.1007/s10479-018-2818-y

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies. *Interactive Technology and Smart Education*, *14*(4), 329-348. https://doi.org/https://doi.org/10.1108/ITSE-06-2016-0015

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Addison-Wesley. http://lib.ugent.be/catalog/rug01:000839739

Flodén, J. (2024). Grading exams using large language models: A comparison between human and AI grading of exams in higher education using ChatGPT. *British Educational Research Journal*, *51*(1), 201–224. https://doi.org/https://doi.org/10.1002/berj.4069

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/10.1177/002224378101800104

Ghimire, A., Imran, M. A. U., Biswas, B., Tiwari, A., & Saha, S. (2024). Behavioral intention to adopt artificial intelligence in educational institutions: A hybrid modeling approach. *Journal of Computer Science and Technology Studies*, *6*(3), 56-64. https://doi.org/https://doi.org/10.32996/jcsts.2024.6.3.6

González-Calatayud, V., Prendes-Espinosa, P., & Roig-Vila, R. (2021). Artificial intelligence for student assessment: A systematic review. *Applied Sciences*, *11*(12). https://doi.org/https://doi.org/10.3390/app11125467

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. M. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education*, *17*(1), 86-106. https://doi.org/https://doi.org/10.1108/ITSE-05-2019-0020

Gunnoo, L., Subadar, U. A., & Fauzel, S. (2023). The mediating effect of attitude on adoption of mobile payment services in small island developing states. The case of Mauritius. *Social Sciences & Humanities Open*, *8*(1), 100724. https://doi.org/https://doi.org/10.1016/j.ssaho.2023.100724

Gupta, K. P., & Bhaskar, P. (2020). Inhibiting and motivating factors influencing teachers' adoption of AI-based teaching and learning solutions: Prioritization using analytic hierarchy process. *Journal of Information Technology Education: Research*, *19*, 693-723. https://doi.org/https://doi.org/10.28945/4640

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage Publications. https://eli.johogo.com/Class/CCU/SEM/_A%20Primer%20on%20Partial%20Least%20Squares%20Structural%20Equation%20Modeling_Hair.pdf

Hakim, M. M., Afifah, A. N., & Aryotejo, G. (2023). The analysis of factors affecting behavioral intention and behavior usage of e-wallet using Meta-UTAUT model. *International Journal on Advanced Science, Engineering and Information Technology*, *13*(2), 786-793. https://doi.org/10.18517/ijaseit.13.2.18297

Harman, H. H. (1976). *Modern Factor Analysis* (3rd ed.). The University of Chicago Press.

Helmiatin, Hidayat, A., & Kahar, M. R. (2024). Investigating the adoption of AI in higher education: A study of public universities in Indonesia. *Cogent Education*, *11*(1). https://doi.org/https://doi.org/10.1080/2331186X.2024.2380175

Henderson, J., & Corry, M. (2021). Teacher anxiety and technology change: A review of the literature. *Technology, Pedagogy and Education*, *30*(4), 573–587. https://doi.org/https://doi.org/10.1080/1475939X.2021.1931426

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

Hermanto, A. H., Windasari, N. A., & Purwanegara, M. S. (2022). Taxpayers' adoption of online tax return reporting: Extended meta-UTAUT model perspective. *Cogent Business & Management*, *9*(1), 2110724. https://doi.org/https://doi.org/10.1080/23311975.2022.2110724

Herodotou, C., Maguire, C., Hlosta, M., & Mulholland, P. (2023, Mar. 2023). Predictive learning analytics and university teachers: Usage and perceptions three years post implementation. LAK23: 13th International Learning Analytics and Knowledge Conference, Arlington, TX, USA.

Hertzog, M. A. (2008). Considerations in determining sample size for pilot studies. *Research in Nursing & Health*, *31*(2), 180-191. https://doi.org/10.1002/nur.20247

Hossain, A., Quaresma, R., & Rahman, H. (2019). Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: An empirical study. *International Journal of Information Management*, *44*, 76-87. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2018.09.016

Huseynov, F., & Özkan Yıldırım, S. (2019). Online consumer typologies and their shopping behaviors in B2C e-commerce platforms. *SAGE Open*, *9*(2). https://doi.org/https://doi.org/10.1177/2158244019854639

IIUM. (2015). *Student academic performance evaluation (undergraduate) regulations 2015*. I. I. U. Malaysia. https://kulliyyah.iium.edu.my/koed/wp-content/uploads/sites/23/2025/10/Student-Academic-Performance-2015-SAPER.pdf

Ishaq, K., Rana, A. M. K., & Zin, N. A. M. (2020). Exploring summative assessment and effects: Primary to higher education. *Bulletin of Educational Research*, *42*(3), 23-50.

JPT. (2022). *Higher education institutions*. Jabatan Pendidikan Tinggi, Kementerian Pendidikan Tinggi, Malaysia. Retrieved Sep. 19 from https://jpt.mohe.gov.my/portal/index.php/en/hei

Kai, C., Ping, W., & Xiaomin, J. (2026). AI anxiety and adoption intention in higher education based on an extended TAM-UTAUT and PLS-SEM analysis. *Scientific Reports*. https://doi.org/10.1038/s41598-026-35823-9

Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. *Sustainability*, *15*(16), 12451. https://www.mdpi.com/2071-1050/15/16/12451

Kannan, R. J., Punithavathi, P., & Sambandam, N. (2018, Nov. 2018). Technology adoption models – adoption of ICT in educational institutions in India. In Proceedings of the 2018 World Engineering Education Forum-Global Engineering Deans Council (WEEF-GEDC), Albuquerque, NM, USA.

Khlaif, Z., Odeh, A., & Bsharat, T. R. K. (2024). Generative AI-powered adaptive assessment. In M. Sanmugam, D. Lim, N. M. Mohd Barkhaya, W. A. J. Wan Yahaya, & Z. Khlaif (Eds.), *Power of Persuasive Educational Technologies in Enhancing Learning* (pp. 157-176). IGI Global. https://doi.org/10.4018/979-8-3693-6397-3.ch007

Kim, K. K., & Prabhakar, B. (2004). Initial trust and the adoption of B2C e-commerce: the case of internet banking. *Data Base for Advances in Information Systems*, *35*(2), 50-64. https://doi.org/10.1145/1007965.1007970

Kleine, A.-K., Kokje, E., Lermer, E., & Gaube, S. (2023). Attitudes toward the adoption of 2 artificial intelligence–enabled mental health tools among prospective psychotherapists: Cross-sectional study. *JMIR Human Factors*, *12*(10), e46859. https://doi.org/10.2196/46859

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling* (T. D. Little, Ed. 4th ed.). Guilford Press. https://books.google.com.my/books?id=EkMVZUxZrgIC

Kothari, C. R. (2004). *Research Methodology: Methods and Techniques* (2nd ed.). New Age International.

Kuen, L., Westmattelmann, D., Bruckes, M., & Schewe, G. (2023). Who earns trust in online environments? A meta-analysis of trust in technology and trust in provider for technology acceptance. *Electronic Markets*, *33*(1), 61. https://doi.org/10.1007/s12525-023-00672-1

Kwak, Y., Ahn, J.-W., & Seo, Y. H. (2022). Influence of AI ethics awareness, attitude, anxiety, and self-efficacy on nursing students' behavioral intentions. *BMC Nurs.*, *21*(1), 267. https://doi.org/https://doi.org/10.1186/s12912-022-01048-0

Kwak, Y., Seo, Y. H., & Ahn, J.-W. (2022). Nursing students' intent to use AI-based healthcare technology: Path analysis using the unified theory of acceptance and use of technology. *Nurse Education Today*, *119*, 105541. https://doi.org/https://doi.org/10.1016/j.nedt.2022.105541

Lee, C. T., & Pan, L.-Y. (2023). Smile to pay: Predicting continuous usage intention toward contactless payment services in the post-covid-19 era. *International Journal of Bank Marketing*, *41*(2), 312-332. https://doi.org/https://doi.org/10.1108/IJBM-03-2022-0130

Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing Research*, *35*(6), 382-386. https://doi.org/https://doi.org/10.1097/00006199-198611000-00017

Machicao, J. C. (2019, Jan. 2019). Higher education challenge characterization to implement automated essay scoring model for universities with a current traditional learning evaluation system. In Á. Rocha, C. Ferrás, & M. Paredes, *Information Technology and Systems* Cham.

Mansour, T. M., & Mansour, H. T. (2025). Employing digital marketers' use of artificial intelligence in jordanian construction companies: An analytical study within the utaut framework. *An-Najah University Journal for Research-B (Humanities)*, *40*(3).

Meidute-Kavaliauskiene, I., Çiğdem, Ş., Yıldız, B., & Davidavicius, S. (2021). The Effect of Perceptions on Service Robot Usage Intention: A Survey Study in the Service Sector. *Sustainability*, *13*(17), 9655. https://www.mdpi.com/2071-1050/13/17/9655

MOE. (2018). *Malaysian education blueprint 2013-2025* (Annual Reports, Issue. M. o. Education. https://www.moe.gov.my/storage/files/shares/Dasar/PPPM/MEB%20Annual%20Report%202018.pdf

Mohamad Mozie, N., Ghazali, N., & Ali Husin, L. I. (2025). Adopting artificial intelligence in higher education: insights from the UTAUT framework on student intentions. *Advances in Business Research International Journal*, *11*(1), 71-79.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192-222. https://doi.org/https://doi.org/10.1287/isre.2.3.192

MOSTI. (2021). *Malaysia national artificial intelligence roadmap 2021-2025 (AI-RMAP 2021-2025)*. T. a. I. Ministry of Science. https://mastic.mosti.gov.my/publication/artificial-intelligence-roadmap-2021-2025/

Nadzirah Muhammad, M., Sri Fatiany Abdul Kader, J., Syukrina Alini Mat, A., & Noor'ain Mohamad, Y. (2025). AI integration in TVET: Examining educators' behavioral intentions and the moderating role of experience. *Information Management and Business Review*, *17*(2(I)S). https://doi.org/10.22610/imbr.v17i2(I)S.4617

Naji, M. G., Elias, N. F., Lam, M. C., Abusamhadana, G. A. O., & Ahmad, N. A. (2022). Big data analytics adoption at higher education institutions in Iraq. *Journal of Theoretical and Applied Information Technology*, *100*(9), 3157-3170.

National AI Office. (2021). *MyDIGITAL Corporation*. National AI Office (NAIO). Retrieved Januarey, 18 from https://ai.gov.my/faq/talent-development-and-education?utm_source=chatgpt.com

National AI Office. (2025). *Building an AI nation to gether, now*. National AI Office (NAIO). Retrieved Januarey, 18 from https://ai.gov.my/

Nuha, A., Gary, W., & Mike, W. (2018). An evaluation of the model of acceptance of e-assessment among academics in Saudi universities. *Education Journal*, *7*(2), 23-36. https://doi.org/https://doi.org/10.11648/j.edu.20180702.11

Oluyinka, S., Endozo, A. N., & Cusipag, M. N. (2021). Integrating trialability and compatibility with UTAUT to assess canvas usage during covid-19 quarantine period. *Asia-Pacific Social Science Review*, *21*(2), 31-47. https://doi.org/https://doi.org/10.59588/2350-8329.1366

Onesi-Ozigagun, O., Ololade, Y. J., Eyo-Udo, N. L., & Ogundipe, D. O. (2024). Revolutionizing education through AI: A comprehensive review of enhancing learning experiences. *International Journal of Applied Research in Social Sciences*, *6*(4), 589-607. https://doi.org/10.51594/ijarss.v6i4.1011

Osman, Z., Alwi, N. H., Jodi, K. H. M., Khan, B. N. A., Ismail, M. N., & Yusoff, Y. (2024). Optimizing artificial intelligence usage among academicians in higher education institutions. *International Journal of Academic Research in Accounting Finance and Management Sciences*, *14*(2), 1–19. https://doi.org/https://doi.org/10.6007/IJARAFMS/v14-i2/20935

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, *39*(2), 230-253. https://doi.org/https://doi.org/10.1518/001872097778543886

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, *54*, 102144. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102144

Pedersen, M. J., & Nielsen, C. V. (2014). Improving survey response rates in online panels: Effects of low-cost incentives and cost-free text appeal interventions. *Social Science Computer Review*, *34*(2), 229-243. https://doi.org/10.1177/0894439314563916

Perez, R. C. L. (2024). AI in higher education: Faculty perspective towards artificial intelligence through UTAUT approach. *Ho Chi Minh City Open University Journal of Science-Social Sciences*, *14*(4), 32-50. https://doi.org/https://doi.org/10.46223/HCMCOUJS.soci.en.14.4.2851.2024

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, *57*, 102207. https://doi.org/https://doi.org/10.1016/j.jretconser.2020.102207

Pinto, A. S., Abreu, A., Costa, E., & Paiva, J. (2023). How machine learning (ML) is transforming higher education: A systematic literature review. *Journal of Information Systems Engineering and Management*, *8*(2), 21168. https://doi.org/10.55267/iadt.07.13227

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531-544. https://doi.org/https://doi.org/10.1177/014920638601200408

Prakash, A. V., & Das, S. (2021). Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: A mixed-methods study. *Information & Management*, *58*(7), 103524. https://doi.org/https://doi.org/10.1016/j.im.2021.103524

Rahman, M. M., Deb, S., Strawderman, L., Burch, R., & Smith, B. (2019). How the older population perceives self-driving vehicles. *Transportation research part F: traffic psychology and behaviour*, *65*, 242-257. https://doi.org/https://doi.org/10.1016/j.trf.2019.08.002

Raosoft, I. (2004). *Raosoft sample size calculator*. Retrieved Jul. 10 from http://www.raosoft.com/samplesize.html

Rigopoulos, G. (2022). Assessment and feedback as predictors for student satisfaction in UK higher education. *International Journal of Modern Education and Computer Science*, *14*(5), 1-9. https://doi.org/https://doi.org/10.5815/ijmecs.2022.05.01

Roh, T., Park, B. I., & Xiao, S. (2023). Adoption of AI-enabled robo-advisors in fintech: Simultaneous employment of UTAUT and the theory of reasoned action. *Journal of Electronic Commerce Research*, *24*(1), 29-47.

Roy, S. K., Singh, G., & Shabnam, S. (2021). Modelling customer engagement behaviour in smart retailing: Modelling customer engagement behaviour. *Australasian Journal of Information Systems*, *25*. https://doi.org/https://doi.org/10.3127/ajis.v25i0.2967

Salloum, S. A. (2024). Trustworthiness of the AI. In A. Al-Marzouqi, S. A. Salloum, M. Al-Saidat, A. Aburayya, & B. Gupta (Eds.), *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 643-650). Springer. https://doi.org/10.1007/978-3-031-52280-2_41

Saman, H. M., Noor, S. M., Isa, C. M. M., Lian, O. C., & Narayanan, G. (2024, 2024-11-30T16:00:00.000Z). Embracing Artificial Intelligence as a catalyst for change in reshaping Malaysian higher education in the digital era: A literature review.

Sánchez-Prieto, J. C., Cruz-Benito, J., Therón, R., & García-Peñalvo, F. J. (2019). How to measure teachers' acceptance of AI-driven assessment in eLearning: A TAM-based proposal. In the Proceedings of the 7th International Conference on Technological Ecosystems for Enhancing Multiculturality, León, Spain.

Sarker, P., Hughes, D. L., & Dwivedi, Y. K. (2020, May. 2020). Extension of META-UTAUT for examining consumer adoption of social commerce: Towards a conceptual model. In F. J. Martínez-López & S. D'Alessandro, Advances in Digital Marketing and eCommerce (DMEC 2020), Cham.

Sekaran, U., & Bougie, R. (2016). *Research Methods For Business: A Skill Building Approach* (7th ed.). John Wiley & Sons.

Seo, K. H., & Lee, J. H. (2021). The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction. *Sustainability*, *13*(8), 4431. https://www.mdpi.com/2071-1050/13/8/4431

Shahid, M. K., Zia, T., Bangfan, L., Iqbal, Z., & Ahmad, F. (2024). Exploring the relationship of psychological factors and adoption readiness in determining university teachers' attitude on AI-based assessment systems. *The International Journal of Management Education*, *22*(2), 100967. https://doi.org/https://doi.org/10.1016/j.ijme.2024.100967

Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023). *Educator and student perspectives on the impact of Generative AI on assessments in higher education* Proceedings of the Tenth ACM Conference on Learning, Copenhagen, Denmark. https://doi.org/10.1145/3573051.3596191

So, S., Ismail, M. R., & Jaafar, S. (2021). Exploring acceptance of artificial intelligence amongst healthcare personnel: a case in a private medical centre. *Int. J. Adv. Eng. Manag, 3,* 56-65.

Song, J. (2024). Integrating artificial intelligence in smart course design: Innovative teaching methods for talent cultivation in higher education. *Education Insights*, *1*(1), 10-16. https://doi.org/10.70088/63t0zj06

Sporrong, E., McGrath, C., & Cerratto Pargman, T. (2025). Situating AI in assessment—an exploration of university teachers' valuing practices. *AI and Ethics*, *5*(3), 2381-2394. https://doi.org/10.1007/s43681-024-00558-8

Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. *Sustainable Development*, *33*(2), 1921–1947. https://doi.org/https://doi.org/10.1002/sd.3221

Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P. (2024). Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies*, *29*(17), 22943-22968. https://doi.org/https://doi.org/10.1007/s10639-024-12765-1

Sue, V., & Ritter, L. (2012). *Conducting Online Surveys* (2nd ed.). Sage Publications. https://doi.org/https://doi.org/10.4135/9781506335186

Tabachnick, B. G., & Fidell, L. S. (2013). *Using Multivariate Statistics* (6th ed.). Pearson Education. https://books.google.com.my/books?id=ucj1ygAACAAJ

Taherdoost, H. (2016). Sampling methods in research methodology; How to choose a sampling technique for research. *International Journal of Academic Research in Management*, *5*(2), 18-27. https://doi.org/https://doi.org/10.2139/ssrn.3205035

Tamilmani, K., Rana, N. P., Nunkoo, R., Raghavan, V., & Dwivedi, Y. K. (2022). Indian travellers' adoption of Airbnb platform. *Information Systems Frontiers*, *24*(1), 77-96. https://doi.org/https://doi.org/10.1007/s10796-020-10060-1

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the Theory of Planned Behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing*, *12*(2), 137-155. https://doi.org/https://doi.org/10.1016/0167-8116(94)00019-K

Teo, T. (2018). Students and teachers' intention to use technology: Assessing their measurement equivalence and structural invariance. *Journal of Educational Computing Research*, *57*(1), 201-225. https://doi.org/https://doi.org/10.1177/0735633117749430

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15*(1), 125-143. https://doi.org/10.2307/249443

U.S. Department of Education, Office of Educational Technology. (2023). *Artificial intelligence and future of teaching and learning: Insights and recommendations*. https://www.ed.gov/sites/ed/files/documents/ai-report/ai-report.pdf

Upadhyay, N., Upadhyay, S., Abed, S. S., & Dwivedi, Y. K. (2022). Consumer adoption of mobile payment services during COVID-19: Extending meta-UTAUT with perceived severity and self-efficacy. *International Journal of Bank Marketing*, *40*(5), 960-991. https://doi.org/https://doi.org/10.1108/IJBM-06-2021-0262

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315. https://doi.org/http://dx.doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. A. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies *Management science*, *46*(2), 186-204. https://ssrn.com/abstract=4062393

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/https://doi.org/10.2307/30036540

Wang, L., & Dai, X. (2020). Exploring factors affecting the adoption of mobile payment at physical stores. *International Journal of Mobile Communications*, *18*(1), 67-82. https://doi.org/https://doi.org/10.1504/IJMC.2020.104420

Wang, S., Yu, H., Hu, X., & Li, J. (2020). Participant or spectator? Comprehending the willingness of faculty to use intelligent tutoring systems in the artificial intelligence era. *British Journal of Educational Technology*, *51*(5), 1657-1673. https://doi.org/https://doi.org/10.1111/bjet.12998

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education: An analysis of teachers perspectives using structural equation modeling. *Educational Technology & Society*, *24*(3), 116-129.

Wanner, J., Herm, L.-V., Heinrich, K., & Janiesch, C. (2022). The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study. *Electronic Markets*, *32*(4), 2079-2102. https://doi.org/https://doi.org/10.1007/s12525-022-00593-5

Wiafe, I., Koranteng, F. N., Tettey, T., Kastriku, F. A., & Abdulai, J.-D. (2020). Factors that affect acceptance and use of information systems within the maritime industry in developing countries: The case of Ghana. *Journal of Systems and Information Technology*, *22*(1), 21-45. https://doi.org/https://doi.org/10.1108/JSIT-06-2018-0091

Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, *21*(1), 40. https://doi.org/10.1186/s41239-024-00468-z

Xiong, Y., Shi, Y., Pu, Q., & Liu, N. (2023). More trust or more risk? User acceptance of artificial intelligence virtual assistant. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *34*(3), 190-205. https://doi.org/https://doi.org/10.1002/hfm.21020

Yang, Q., Al Mamun, A., Hayat, N., Jingzu, G., Hoque, M. E., & Salameh, A. A. (2022). Modeling the intention and adoption of wearable fitness devices: A study using SEM-PLS analysis. *Frontiers in Public Health*, *10*, 918989. https://doi.org/https://doi.org/10.3389/fpubh.2022.918989

Ye, X., & Manoharan, S. (2018). Machine learning techniques to automate scoring of constructed-response type assessments. In the Proceedings of the 28th EAEEIE Annual Conference, Hafnarfjordur, Iceland.

Yedilbayev, Y., Sarybayeva, A., Zharylgapova, D., Shektibayev, N., Usembayeva, I., & Kurbanbekov, B. (2023). Factors influencing future physics teachers' acceptance of information and communicative competence technologies: A survey study. *Cogent Education*, *10*(1), 2212119. https://doi.org/https://doi.org/10.1080/2331186X.2023.2212119

Zaim, M., Arsyad, S., Waluyo, B., Ardi, H., Al Hafizh, M., Zakiyah, M., Syafitri, W., Nusi, A., & Hardiah, M. (2024). AI-powered EFL pedagogy: integrating Generative AI into university teaching preparation through UTAUT and activity theory. *Computers & Education: Artificial Intelligence*, *7*, 100335. https://doi.org/https://doi.org/10.1016/j.caeai.2024.100335

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*(1), 8812542.