

## Research

# Understanding the role of AI in Malaysian higher education curricula: an analysis of student perceptions

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## Abstract

This study explores the role of Artificial Intelligence (AI) in higher education curricula, focusing on student perceptions and engagement with AI tools through the lens of key variables: perceived utility, satisfaction, content quality, and perceived credibility. The rapid adoption of AI technologies, such as intelligent tutoring systems and adaptive learning platforms, offers significant promise in enhancing personalized learning, improving content delivery, and streamlining administrative processes. However, successfully integrating AI into higher education requires an understanding of how students perceive these tools and how their perceptions influence adoption. The study employs a quantitative cross-sectional survey design and utilizes Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the relationships between the identified predictors and students' use of AI in their academic experiences, based on data from 306 participants. The results reveal that satisfaction has the strongest impact on students' use of AI in higher education curricula, highlighting the importance of providing user-friendly, reliable, and effective platforms. The perceived utility also plays a significant role, though its effect size is moderate, indicating that while students recognize AI's potential benefits in achieving academic goals, other factors also contribute to their willingness to adopt these tools. Content quality and perceived credibility, while positively correlated with AI adoption, were found to have weaker and statistically non-significant effects. This suggests that students may prioritize functionality and user experience over content quality and trust in AI systems. The study's findings provide valuable insights for educators and policymakers aiming to optimize AI adoption in higher education curricula, emphasizing the need for comprehensive strategies that address multiple factors influencing student perceptions.

**Keywords** Artificial Intelligence · Satisfaction · Perceived utility · Content quality · Perceived credibility

## 1 Introduction

The rapid integration of Artificial Intelligence (AI) into higher education is transforming how curricula are designed, delivered, and received. Educational institutions increasingly leverage AI-based tools to enhance learning experiences, promote personalized education, and improve operational efficiency. These technologies, including adaptive learning platforms, intelligent tutoring systems, and generative AI applications, promise to revolutionize teaching

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and learning by aligning educational content with students' needs, thus boosting engagement and knowledge retention [2]. In the context of the Malaysian education system, AI is gradually being incorporated to support both educators and students. The Malaysian higher education sector is undergoing rapid digital transformation, driven by government initiatives such as the Malaysia Education Blueprint 2015–2025 emphasising the integration of emerging technologies in higher education [35]. Universities and colleges are adopting AI-driven solutions to automate administrative tasks, develop smart assessment methods, and provide real-time feedback to learners [6]. Additionally, AI-powered language processing tools are assisting students in overcoming language barriers, particularly in a multilingual society like Malaysia.

However, while AI presents numerous opportunities, challenges such as digital infrastructure gaps, data privacy concerns, and the need for educator upskilling remain significant hurdles to widespread adoption. Institutions face the complex task of embedding AI meaningfully into curricula while maintaining academic integrity and aligning with pedagogical standards. For instance, while AI tools can greatly improve content delivery and customization, they often face scepticism regarding their credibility and reliability, affecting their perceived utility among students. AI-based tools are increasingly used for delivering academic content and assessment, yet students frequently question the reliability and trustworthiness of AI-generated feedback. This concern is further intensified by the opacity of AI algorithms, which might hinder students' trust and affect their willingness to rely on these systems for critical academic tasks [5, 13]. These limitations may impact students' perception of the overall quality and effectiveness of AI as a learning tool, ultimately influencing their engagement and satisfaction with AI-integrated curricula.

In addition, although AI's adaptive capabilities are expected to enhance personalized learning experiences, the quality and reliability of AI-generated content are frequently questioned. Almufarreh [7] highlights that while AI can customize learning paths, it may lack the contextual understanding to provide quality feedback and nuanced academic insights. This potential limitation may impact students' perception of the overall quality and effectiveness of AI as a learning tool, which in turn could affect their engagement and satisfaction with AI-integrated curricula. The perceived utility also presents a nuanced gap, as students' perceptions of AI's educational value are not uniform across disciplines or educational contexts. For instance, Jacobs et al. [24] found that the perceived utility of AI tools varies significantly based on students' familiarity with technology and their academic field, suggesting that perceived utility is influenced not only by AI's technical capabilities but also by users' baseline expectations and academic requirements. Hence, Saihi et al. [55] stated that to maximize the potential of AI, universities must ensure these technologies are seen as valuable, credible, and enhancing the educational experience. Neglecting these concerns could lead to low engagement with AI tools and a diminished return on institutional investments in AI.

Despite the growing integration of Artificial Intelligence (AI) in higher education, the research gap persists, particularly regarding how students perceive and interact with AI-enabled tools across key dimensions: curricula integration, satisfaction, perceived credibility, content quality, and perceived utility. Existing studies [3, 31, 55] frequently highlight AI's potential to enrich educational experiences and its operational benefits, but empirical research remains limited on how these dimensions influence students' long-term acceptance and effective utilisation of AI [31]. One notable gap lies in understanding the perceived credibility of AI tools in educational settings. Empirical studies that examine how perceived credibility affects the adoption and satisfaction levels of AI-driven educational tools are scarce, highlighting the need for further investigation into how AI transparency and reliability enhance students' trust in these tools [55]. Furthermore, most research on AI in education has been conducted in Western contexts, where digital literacy levels, institutional infrastructure, and student attitudes toward AI differ from those in Malaysia [18, 31].

To date, localised empirical research on student perceptions of AI integration in Malaysian higher education remains scarce, particularly regarding perceived utility, satisfaction, content quality, and credibility. This gap contrasts sharply with the predominance of Western-centric studies in the field and highlights the urgent need for Malaysia-specific data to inform AI curriculum development. Ensuring that integration strategies are grounded in contextually relevant evidence is essential [31, 33, 67]. The unique socio-cultural and academic landscape of Malaysian higher education necessitates localised research that examines AI adoption, student trust in AI-generated content, and how institutional policies impact students' engagement with AI-driven learning tools. Also, by focusing on the Malaysian context, this study offers a nuanced understanding of how AI adoption aligns with national educational policies, institutional digital strategies, and student expectations. Lastly, while there is substantial literature on general student satisfaction with e-learning tools, limited research specifically addresses satisfaction with AI-based platforms. Many existing studies focus on the functional aspects of satisfaction, such as ease of use or accessibility, rather than delving into satisfaction derived from AI-specific attributes like adaptive learning and predictive capabilities [31]. Given that satisfaction is a critical factor in technology adoption, further research is needed to assess how AI-driven learning

experiences align with students' expectations and contribute to positive academic outcomes. The findings will inform policymakers, educators, and AI developers on how to design AI-enabled curricula that cater to students' learning preferences and concerns, ultimately leading to more effective and engaging AI integration in Malaysian universities.

## 2 Literature review

### 2.1 Theoretical framework of the studies

The Technology Acceptance Model (TAM), developed by Davis [17], is a widely recognized theoretical framework in educational research that explains how individuals adopt and use technology. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the primary determinants of technology acceptance. In the field of education, TAM has been extensively applied to investigate students' and educators' acceptance of emerging technologies, including e-learning platforms, artificial intelligence (AI), and digital learning tools, by examining how their perceived benefits influence usage behaviour [50]. Within the context of AI integration in higher education, the Perceived Utility of AI (PUAI) is conceptually aligned with Perceived Usefulness (PU) in TAM, referring to an individual's belief that AI enhances learning efficiency, problem-solving capabilities, and overall academic performance. According to TAM, when individuals perceive AI as beneficial for their educational activities, they are more likely to adopt and integrate it into their learning and teaching practices, which refers to the use of AI in Higher Education Curricula (UAIHEC).

In this study, UAIHEC is operationalized as the extent to which students and educators incorporate AI technologies into their academic activities. Based on the theoretical foundation of TAM, PUAJ is expected to serve as a key predictor of UAIHEC, as individuals who perceive AI as a valuable educational tool are more inclined to engage with it. The underlying rationale is that when AI is perceived to enhance learning outcomes and facilitate academic processes, its adoption within higher education curricula will increase. Consequently, this study hypothesizes that PUAJ has a positive influence on UAIHEC, thereby reinforcing TAM's core proposition that perceived benefits significantly shape technology adoption in educational settings. TAM's applicability continues to be validated in recent AI adoption research. For instance, Mustofa et al. [43] extended the TAM by incorporating ethics and trust to study university students' adoption of AI tools, revealing that Perceived Usefulness remained a significant predictor of attitude, whereas Perceived Ease of Use was not statistically influential due to students' high familiarity with technology. Furthermore, the inclusion of ethical considerations in this model highlighted that beyond usability, factors such as perceived fairness and trustworthiness of AI systems can directly shape students' attitudes and willingness to use AI [43].

The Expectation-Confirmation Model (ECM), originally proposed by Bhattacharjee [12], is a theoretical model widely used in educational technology research to explain continuance intention where the decision to continue using a particular technology. ECM posits that users' satisfaction with technology is shaped by their expectations before use and the confirmation of those expectations after use [54]. In this study, Satisfaction (SA) is defined as the degree to which students and educators feel content with AI's performance in educational contexts. Additionally, expectation is influenced by the Perceived Credibility of AI (PCAI) and the Content Quality of AI (CQAI). Research indicates that perceived credibility significantly influences user expectations within the Expectation-Confirmation Model, particularly in technology and information-based contexts [57]. Studies have shown that when users perceive a source as credible, they develop higher expectations about the information or service provided, leading to greater satisfaction upon confirmation [26], ultimately influencing satisfaction and continued technology adoption. Another key concept correlated with expectation is content quality. High-quality content has been shown to positively influence user satisfaction and expectations. Many researchers posit that when the quality of content meets or surpasses user expectations, it results in positive user satisfaction and the likelihood of continued engagement [28].

Since expectations play a key role in determining satisfaction and future adoption, PCAI and CQAI are included as antecedents of SA. Therefore, PCAI and CQAI are expected to influence UAIHEC through expectation confirmation, as users who perceive AI as credible and delivering high-quality content are more likely to integrate it into their learning environments. Empirical findings further support ECM's focus on satisfaction and confirmation. For example, research on e-learning continuance consistently shows that user satisfaction is one of the strongest predictors of ongoing technology use, often outweighing initial perceived usefulness once students have actual usage experience [7]. In the context of AI-based educational tools, when students' expectations are met or exceeded, such as through accurate, relevant content and reliable performance, they report higher satisfaction and a greater likelihood of continuing to use the AI system

[7]. Thus, aligning AI outcomes with student expectations (e.g., delivering quality content and credible information) is crucial for sustaining long-term adoption, as predicted by ECM.

## 2.2 Development of Artificial Intelligence in education

Artificial Intelligence (AI) has gradually emerged in education, with its origins tracing back to the mid-twentieth century. The integration of this tool has garnered significant attention over the past two decades. In Malaysia, it demonstrated a growing commitment to the integration of AI in higher education, aligning with the national agenda for digital transformation. The Malaysian Ministry of Higher Education (MOHE) has recognized AI as a critical enabler for improving teaching, learning, and administrative processes in universities.

Several studies have explored AI integration in Malaysian education. For example, Mustapha et al. [42] assessed the AI knowledge and competency of 81 vocational teacher trainers in Malaysia's Design and Technology program. Using surveys and thematic analysis, the findings revealed low AI knowledge and skills among respondents, suggesting the need for more AI-related courses in vocational training. The study recommended revising the TVET curriculum to include AI-based content, highlighting the importance of equipping vocational students with AI competencies to meet future industry demands. Another study by Ng [46] examined factors of AI tools affecting Malaysian undergraduate students' academic writing proficiency. Key factors analysed were personalized learning, feedback mechanisms, usage frequency, and hedonic motivation. Using a survey of 200 students, the findings revealed that personalized learning, feedback mechanisms, and hedonic motivation significantly enhance academic writing proficiency, with feedback mechanisms having the greatest impact. The study emphasized that students found AI tool feedback to provide valuable support, playing a crucial role in improving their writing skills.

Additionally, a study by Wang and Shi [65] explored the acceptance and use of AI in history education among Malaysian university students. Utilising the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, a survey among 512 students from four Malaysian universities was analysed with Partial Least Squares-Structural Equation Modelling. The study found a significant influence of behavioural intention to use AI on actual use while facilitating conditions had no significant effect on usage behaviour. The model explained 43.7% of the variance in behavioural intention, extending UTAUT's application to humanities education and providing practical insights for integrating AI tools in history education. Interestingly, other Malaysian studies suggest that supportive conditions can matter for AI acceptance. For instance, Foroughi et al. [20] examined university students' intention to use ChatGPT in Malaysia and found that facilitating conditions (e.g., access to technology and guidance) positively impacted their behavioural intention to adopt the AI chatbot [19]. This discrepancy indicates that the influence of external support and infrastructure may vary depending on the specific educational context and type of AI tool, highlighting the need to tailor integration strategies accordingly.

The transformative potential of generative AI in Malaysian higher education has also been highlighted. Saman et al. [56] focused on AI's ability to personalize learning, foster digital inclusion, and empower educators. Tools like ChatGPT, Copilot, Gemini, and Claude can tailor learning experiences through customized feedback, expand educational access for diverse learners, and enhance teaching effectiveness by supporting content creation and collaborative projects. Likewise, Amdan et al. [10] found that AI-powered tools can offer personalized instruction, intelligent tutoring, and interactive simulations, while also automating tasks like grading and providing predictive analytics to enhance efficiency in STEM classrooms. Their study highlights AI's potential to improve student mastery, boost motivation and autonomy, and enable teachers to offer more personalized support.

In a broader context, AI integration in education has been recognized globally. For example, a study by Chisom et al. [15] highlights AI's contributions in overcoming language barriers, improving literacy, fostering digital skills, and supporting teachers through professional development and administrative tools in Africa. The study found that AI integration in education has helped bridge gaps in access and quality, promoting inclusive education across continents. Key applications of AI include adaptive learning platforms, virtual tutors, and intelligent content delivery systems that cater to diverse student needs. Ma et al. [32] further examined how cultural backgrounds influence students' attitudes and intentions toward using AI in higher education, comparing Chinese and international students. Using TAM and survey data analyzed via SEM, the research identified significant differences between the two groups. International students showed a stronger correlation between perceived ease of use and their attitudes/intention to adopt AI compared to Chinese students. The findings highlight the impact of cultural background and prior technology exposure on AI perceptions, emphasizing the need for tailored educational strategies such as language-specific support and user-friendly interfaces to accommodate diverse perspectives. These insights guide educators and institutions in effectively integrating AI into teaching and learning.

In parallel, the emergence of advanced generative AI tools (like ChatGPT) in education has spurred large-scale investigations into student adoption patterns worldwide. Ravšelj et al. [53] conducted a global survey of over 23,000 higher education students across 109 countries, revealing that students widely utilize ChatGPT for tasks such as brainstorming ideas and summarizing content. Notably, while many students found ChatGPT useful for enhancing their learning efficiency, there were prevalent concerns regarding its reliability and the potential for academic misconduct [53]. This global study underscores a common theme: students perceive clear benefits of AI for learning, yet they simultaneously call for oversight and improvements to ensure content quality and ethical use. Similarly, a regional study in Sweden by Stöhr et al. [60] found broad awareness and generally positive attitudes toward AI chatbots among university students. However, it is also documented significant apprehension among certain groups (e.g., female and humanities students) about AI's impact on learning and assessment fairness. These empirical insights from different parts of the world emphasize that successful AI integration in curricula requires not only leveraging its perceived utility but also addressing students' trust and comfort with the technology.

Jain and Jain [25] provide a complementary perspective by exploring the role of AI in transforming teaching and learning in higher education. Their study examines how AI can improve learning experiences both inside and outside the classroom, making education more accessible and efficient. Focusing on higher education institutions in Udaipur, India, and using structured questionnaires to gather teachers' perceptions, the findings reveal that AI significantly enhances students' learning capabilities and holds great potential for future growth in the higher education sector. The study also identifies challenges in implementing AI and provides valuable insights for educators and educational policy development.

### 2.3 The role of Artificial Intelligence in higher education curricula

The role of AI in higher education has generated significant interest among scholars, educators, and policymakers, given AI's potential to transform learning experiences, streamline administrative processes, and improve student outcomes. AI's applications in higher education span a broad range of functionalities, including intelligent tutoring systems, predictive analytics for student performance, and content customization [31]. However, despite its promise, the integration of AI into higher education requires critical examination, particularly regarding its effectiveness in fostering authentic engagement and educational value.

One of the primary promises of AI in education is its ability to provide personalized learning experiences. Intelligent tutoring systems and adaptive learning platforms analyze data to adjust content delivery based on individual learning styles, helping students master material at their own pace [61, 39]. By responding to individual needs, these technologies aim to enhance engagement and improve academic outcomes, yet questions arise regarding the depth and quality of such personalization [33, 38]. Critics argue that while AI can identify gaps in knowledge and adaptively present content, it may lack the capacity for nuanced interpretation and feedback, which are essential for critical thinking development. Thus, while AI enhances efficiency, its efficacy in supporting deep learning processes remains contentious.

In addition to personalization, AI plays a substantial role in administrative tasks, including predictive analytics to identify at-risk students and optimize resource allocation. This capacity for data-driven insights has been applauded for its potential to enhance institutional decision-making. However, ethical concerns regarding data privacy, algorithmic bias, and the transparency of AI-driven predictions present substantial barriers to widespread acceptance. Galdames [21] underscores that while AI can streamline administrative processes, it may also introduce issues related to student privacy and accountability in decision-making, challenging institutions to balance innovation with ethical responsibility. Ensuring that AI systems are transparent, fair, and secure is essential for maintaining trust among stakeholders.

Finally, the advent of generative AI (e.g., large language models like ChatGPT) brings both opportunities and challenges to higher education curricula. These tools can assist in content creation, provide real-time feedback, and facilitate independent learning, but they also raise questions about academic integrity and the role of human educators. The key challenge lies in integrating AI in ways that complement and enhance human instruction rather than replace it. This necessitates ongoing dialogue and research into best practices for AI-assisted education, ensuring that the technology is used to enrich learning outcomes while upholding educational values.

### 2.4 Perceived utility of AI in higher education curricula

Central to the successful adoption of AI in education is the construct of Perceived Utility. This construct refers to stakeholders' beliefs about the usefulness and effectiveness of AI in improving educational outcomes. According to Davis [17], perceived utility (analogous to perceived usefulness) is the degree to which users believe a technology

will enhance their performance. Applied to the education system, the Perceived Utility of Artificial Intelligence (PUAI) reflects how students, educators, and administrators view the value of AI technologies in supporting teaching, learning, and operational efficiency. Lijie et al. [31] stated that PUAJ encompasses several dimensions including academic utility—referring to benefits such as personalised learning, adaptive assessments, and intelligent tutoring systems. Moreover, Saxena et al. [58] explain that PUAJ also includes operational utility, which streamlines administrative tasks like enrolment, grading, and resource allocation. This construct also highlights research utility, which is the capability of AI to enhance data analysis and foster interdisciplinary research. Through these dimensions, PUAJ can directly influence UAIHEC. Venkatesh et al. [64] posited that positive perceptions of a technology's usefulness enhance its integration into institutional practices. Recent studies have confirmed this relationship in educational contexts. For example, Rana et al. [51] found that clear communication of AI's benefits within an institution enhanced adoption rates—institutions with strong messaging about AI's advantages experienced higher adoption levels among faculty and students. Similarly, Ng et al. [44] found that the positive effects of PUAJ correlated with the successful implementation of AI tools, leading to better academic performance.

Consistent with these findings, numerous empirical studies have reaffirmed the importance of perceived utility in student acceptance of AI. Kanont et al. [27] observed that the expected benefits and Perceived Usefulness of generative AI tools significantly influenced Thai university students' attitudes and intentions to adopt those tools. In another study, Al-Abdullatif and Alsubaie [4] similarly found that students' intentions to use ChatGPT were strongly linked to the perceived value the AI provided to their learning process, especially among students with higher AI literacy. These cases highlight that when learners clearly recognize the value added by AI whether through improved learning outcomes, efficiency, or support, their propensity to integrate such technologies into their studies increases significantly.

**H1** PUAJ has a significant and positive impact on UAIHEC.

## 2.5 Satisfaction and content quality of AI in higher education curricula

Other critical factors influencing the success of AI integration include satisfaction with how students, educators, and administrators perceive and respond to AI-driven tools and content quality with the relevance, accuracy, and pedagogical effectiveness of AI-generated content. According to Almufarreh [7], satisfaction refers to the overall contentment of stakeholders regarding the use of AI tools in learning and teaching processes. In educational technology, satisfaction is a multidimensional construct involving perceptions of ease of use, effectiveness, and even emotional engagement with AI-based systems. Similarly, content quality relates to the characteristics of AI-generated or AI-curated educational materials, including their accuracy, relevance, interactivity, and adaptability to learners' needs [68]. High-quality content is critical for fostering trust in AI systems and ensuring meaningful learning experiences.

Many studies have highlighted a strong, positive relationship between satisfaction and content quality in AI-driven educational contexts. Most findings consistently show that high-quality content drives higher levels of satisfaction among students and educators. For example, Chen et al. [14] found that students were more likely to recommend AI learning tools when they perceived the content as accurate and pedagogically effective. Similarly, Basri [11] observed that student satisfaction increased significantly in online courses where AI tools curated well-organized, research-based content.

Further, recent analytics-driven studies provide quantitative evidence of this link. Almufarreh [7], using a PLS-SEM approach, confirmed that the content quality of AI outputs and the perceived utility of AI tools were significant predictors of students' satisfaction with those tools, together accounting for a substantial portion of the variance in satisfaction. In practical terms, students are much more satisfied when AI systems deliver accurate, relevant content and tangibly aid their learning objectives. Moreover, research on AI-driven tutoring systems has noted that enhancing content clarity and alignment with course objectives can boost student satisfaction and engagement levels [8]. These findings reinforce that high-quality, pedagogically sound AI content is a prerequisite for positive user experiences, which in turn encourages continued use and peer recommendations of AI-based tools in education.

**H2** SA has a significant and positive impact on UAIHEC.

**H3** CQAI has a significant and positive impact on UAIHEC.

## 2.6 Perceived credibility and trustworthiness of AI tools in higher education curricula

The perceived credibility and trustworthiness of AI tools is another crucial construct that drives the success of AI integration in education. Perceived credibility refers to users' belief in the accuracy, reliability, and competence of AI tools. Ou et al. [49] note that credibility in technology can be divided into surface credibility (appearance-based trust) and earned credibility (trust established through performance). In the context of AI, factors like content accuracy, clarity, and alignment with academic standards contribute to perceived credibility [30]. Trustworthiness, on the other hand, encompasses users' confidence in AI systems to perform consistently, securely, and ethically. It includes perceptions of fairness, privacy, and the absence of bias in AI operations. Mayer et al. [34] propose a framework for trust that includes ability, integrity, and benevolence, all of which are critical in evaluating AI education tools.

Several studies suggest that credibility and trustworthiness are interdependent in influencing adoption. For instance, Shin [59] noted that accurate and reliable AI systems earned credibility, which in turn fostered trust among users. Similarly, transparent and fair operations increased trustworthiness and reinforced users' perceptions of system credibility. In educational settings, Mogavi et al. [40] found that students were more willing to adopt AI-powered learning platforms when they trusted the tools to deliver high-quality, credible content illustrating how trust and perceived content credibility work together to encourage usage.

Empirical evidence across contexts further underscores the importance of trust in AI's outputs for driving adoption. Abdalla [1] found that higher education students' trust in ChatGPT was a significant positive predictor of their continued use of the AI, whereas concerns (i.e., perceived risks) had an adverse effect on their usage intentions. This highlights that when AI tools demonstrate reliability and transparency and align with users' values (thereby earning trust), students are far more inclined to embrace them in their academic routines. In a similar vein, Mustofa et al. [43] emphasize that incorporating trust-building measures and ethical safeguards in AI tools can enhance student attitudes and acceptance, suggesting that credibility and trustworthiness need to be proactively cultivated. Notably, Malaysian-based research on AI adoption also underscores infrastructure and support as components of credibility; when students feel that an AI platform is well-supported and endorsed by their institution, their confidence in using it grows [20]. Ultimately, fostering a high degree of trust in AI systems—by ensuring consistent performance, accuracy, and ethical design—is essential for their sustainable integration into higher education.

**H4** PCAI has a significant and positive impact on UAIHEC.

## 3 Methodology

### 3.1 Participants

Following the guidelines provided by G\*Power and the "10-times rule," as suggested by Hair et al. [22], the required sample size for this study was calculated to be 85 participants, aimed at examining predictors of AI adoption in higher education curricula. Additionally, to account for potential non-response [37], an additional 25% was included, leading to an invitation of 21 more participants.

Since the instruments used in this study had not previously been validated within this research context, a Confirmatory Factor Analysis (CFA) was deemed necessary to ensure the instruments' validity. In accordance with Kline [29], who recommends a minimum sample size of 200 for CFA in Structural Equation Modeling (SEM), a total of 200 participants were specifically recruited for this validation process before the main study. Consequently, a total of 306 participants were targeted, comprising 200 for CFA and 106 for the main study.

The decision to recruit this sample size further supported by the need to ensure adequate statistical power and model stability in SEM analyses. Wolf et al. [66] highlighted that sample size requirements for SEM vary widely, ranging from 30 to 460 cases, depending on model complexity and desired statistical power. Therefore, securing a sample size of 306 participants aligns with these recommendations, aiming to balance model complexity with sufficient statistical power.

Participants were recruited via simple random sampling from public universities, facilitated through group emails and networks involving colleagues who are educators. Data collection spanned 2 months, with ethical approval secured from the relevant ethics committee at Universiti Malaya. An introductory email provided students with

information about the study's purpose, emphasized the voluntary nature of participation, and assured confidentiality of responses. Ultimately, 306 valid responses were obtained and were utilized for subsequent analysis in this research.

### 3.2 Instruments

In this study, five key instruments were employed: the Use of AI in Higher Learning Curricula Scale, Satisfaction Scale, Perceived Credibility of AI Tools Scale, Content Quality of AI Tools Scale, and Perceived Utility of AI Tools Scale. To enhance both the feasibility and validity of these instruments for respondents whose primary language is not English, all instruments were presented in a bilingual format. While the core content of the tools remained intact, specific contextual references to "AI learning tools" were adapted. A rigorous content validation process was undertaken, which included blind back-translation, expert review, and pilot testing. Two English translation experts carried out the blind back-translation to ensure accuracy. Subsequently, a panel of six subject-matter experts evaluated the content for alignment and validity.

For the pilot test, 200 participants who were not part of the main study were recruited, and Confirmatory Factor Analysis (CFA) was employed to evaluate the validity of the instruments. For the independent variables, 10 satisfaction items, 5 perceived credibility items, 5 content quality items, and 7 perceived utility items were all adapted from Almufrreh [7]. The dependent variable, the Use of AI in Higher Learning Curricula Scale, comprised 10 items, as referenced by Ng et al. [45]. Each instrument was structured around a 5-point Likert Scale, ranging from "Strongly Disagree" to "Strongly Agree."

During the CFA for the pilot test, all items exceeded the threshold value (0.7), and thus all the items are retained for the main study. As recommended by Hair et al. [22], reliability and validity were confirmed through Cronbach's alpha and composite reliability values exceeding 0.70. Factor loadings also met the minimum threshold of 0.70, while the AVE for each construct surpassed 0.50, indicating satisfactory convergent validity. For divergent validity, the HTMT ratio of correlations was kept below 0.90, and the square root of the AVE for each construct was greater than its correlations with other constructs. Furthermore, each item's factor loading within its designated construct was higher than any loading it had in related constructs [22].

Following the criteria mentioned, only items that met the specified thresholds were retained for each construct. The final Confirmatory Factor Analysis was conducted separately for each instrument, revealing a strong model fit across the board, as indicated by an SRMR  $\leq 0.08$  and NFI  $\geq 0.9$ . Each construct demonstrated satisfactory Cronbach's alpha and composite reliability values above 0.7, factor loadings above 0.7, and AVE values exceeding 0.5. Additionally, HTMT values were all below 0.9, confirming the validity and reliability of the instruments for the main study. A comprehensive list of retained items is provided in [Appendix](#).

### 3.3 Procedure

Before administering the research instruments to the student participants, the researcher will obtain ethical approval from the relevant ethics committee to ensure compliance with ethical standards. Data collection is expected to last 2 months, during which the instruments will be administered to gather sufficient responses. In the initial phase of analysis, all instruments will undergo validation through separate Confirmatory Factor Analyses (CFA) to confirm their suitability and reliability within this specific research context. This validation step is crucial to establish the robustness of the measurement tools used in assessing the Use of AI in Higher Learning Curricula.

Upon confirming instrument validity, the researcher will employ Structural Equation Modelling (SEM) to analyse the data. SEM was utilised to evaluate both the measurement model, examining the relationships among observed and latent variables within the construct, and the structural model, to identify and analyse the predictive factors of the Use of AI in Higher Learning Curricula. This dual approach in SEM allows for a comprehensive assessment of both the measurement accuracy and the underlying structural relationships, offering insights into which factors most significantly contribute to the Use of AI in Higher Learning Curricula. Such a rigorous approach ensures that the findings can be confidently interpreted in light of the study's objectives, establishing a reliable basis for understanding the predictors of AI adoption in higher education.

### 3.4 Data analysis

This study utilizes a quantitative cross-sectional survey design, which offers several advantages, including the ability to generalize findings, describe the prevalence and characteristics of the target cohort, and test hypothesized relationships at a specific point in time. The sample includes 200 responses for the initial Confirmatory Factor Analysis (CFA) of the instruments, followed by an additional 106 responses for the main analysis, ensuring adequate data for robust statistical testing.

To test the validity and reliability of the instruments and to examine the hypothesized model, Partial Least Squares Structural Equation Modelling (PLS-SEM) was conducted using Smart-PLS 4.0. This approach allows for comprehensive testing of the CFA, the measurement model, and the structural model, providing a nuanced understanding of each component's contribution. The CFA focused on key model fit indices, including assessments of internal reliability, convergent validity, and discriminant validity for each instrument, ensuring that the constructs measured align with the study's theoretical framework.

In assessing the measurement model, six reflective second-order constructs were evaluated holistically for internal reliability, as well as for convergent and discriminant validity [22]. This evaluation enhances the model's robustness, facilitating the examination of the relationships among latent variables. Once the instruments were validated, the structural model was tested, focusing on the relationships between the latent constructs and their impact on the Use of AI in Higher Education Curricula (UAIHEC). The structural model's significance was assessed through bootstrapping, with indices such as p-values ( $p < 0.001$ ), t-values, and path coefficients ( $\beta$ ) guiding the interpretation. The confidence interval, excluding zero, was also examined to verify the significance of the mediating effects.

To gain deeper insights into the predictive capacity of the model, the R2 value (explaining the variance in UAIHEC) and the f2 effect size for each predictor were analysed. This analysis provides an understanding of both the cumulative and individual contributions of the predictors on UAIHEC. Detailed interpretations and implications of these findings will be discussed in the following section, with a focus on how each predictor's effect size informs our understanding of AI integration in higher education settings. This approach underscores the study's commitment to rigorously exploring key factors influencing AI adoption in educational curricula.

## 4 Results

### 4.1 Demographic information

Following the validation of the individual instrument through Confirmatory Factor Analysis (CFA), this section will present the findings from both the measurement model and the structural model. The results are based on data collected from 106 participants who were involved in the main study. Before interpreting the results of PLS-SEM, the demographic information was presented in Table 1.

Table 1 provides a comprehensive overview of the demographic characteristics of the respondents in this study. A total of 106 participants were surveyed, with a higher representation of females (67%) compared to males (33%). In terms of academic level, the majority of respondents were pursuing a Bachelor's degree (57%), followed by Diploma students (28%), Master's degree students (9%), and Doctor of Philosophy candidates (4%). Age-wise, nearly half (49%) of the participants were aged 23–27, while 24% were in the 18–22 age bracket, 14% were aged 28–32, 10% were between 33–37 years old, and only 2% were aged 38 or above. When considering fields of study, the largest groups were Business and Management (23%), Education (20%), and Social Sciences (15%), followed by Health and Medicine (10%), Art and Humanities (9%), Communication and Media (8%), and Law and Public Policy (6%), with 5% from other majors. In terms of AI tools used, all respondents (100%) reported using ChatGPT, while 43% had experience with Gemini, 34% with Microsoft Copilot, 21% with Perplexity, and 12% with DALL-E. Some respondents also reported using Claude (10%), Midjourney (8%), and Bard (6%), reflecting a broad spectrum of AI adoption. Regarding the usage time of AI tools, the majority of respondents (58%) had been using AI for more than 1 year, while 21% had used it for 10–12 months, 10% for 7–9 months, 7% for 3–6 months, and only 3% for less than 3 months. Additionally, the study was conducted in 5 renowned public universities in Klang Valley, Malaysia. These institutions play a vital role in higher education and contribute significantly to academic research and technological advancements in Malaysia.

**Table 1** Demographic information of respondents

Demographic	Clarification	Number	Percentage
Gender	Male	35	33
	Female	71	67
University	University A	35	33
	University B	23	22
	University C	15	14
	University D	19	18
	University E	14	13
Academic level	Diploma	30	28
	Bachelor's Degree	61	57
	Master's Degree	10	9
	Doctor of Philosophy	5	4
Age	18–22	26	24
	23–27	52	49
	28–32	15	14
	33–37	11	10
	38 or above	2	2
Field of study	Art and humanities	10	9
	Social sciences	16	15
	Business and management	25	23
	Education	22	20
	Health and medicine	11	10
	Law and public policy	7	6
	Communication and media	9	8
	Other majors	6	5
AI tools used	ChatGPT	106	100
	Gemini	46	43
	Microsoft Copilot	36	34
	Dall-e	13	12
	Perplexity	23	21
	Claude	11	10
	Midjourney	9	8
	Bard	7	6
Usage time	Less than 3 months	4	3
	3–6 months	7	7
	7–9 months	11	10
	10–12 months	22	21
	More than 1 year	62	58

This demographic data highlights a diverse and representative sample of students encompassing various academic disciplines and differing levels of AI experience across different stages of education.

## 4.2 Normality and descriptive statistic

The target population for this study consisted of students from universities in Selangor who are exposed to AI in the higher education curricula. Using simple random sampling [41, 62], a total of 106 valid responses were collected. Before conducting the main analysis, the dataset was assessed for normality by evaluating skewness and kurtosis values. According to theoretical guidelines, skewness and kurtosis values should fall within the range of  $-2$  to  $+2$  [48]. The results confirmed the data's normality, with kurtosis values ranging from  $-0.452$  (UAIHLC10) to  $1.282$  (SA4) and skewness values ranging from  $-1.16$  (UAIHLC4) to  $-0.019$  (UAIHLC10). Additionally, descriptive statistics, including mean ( $\bar{x}$ ) and standard deviation (SD), were reported for all items (Table 2). The mean values

**Table 2** Mean, SD, kurtosis, skewness

	$\bar{x}$	SD	Skewness	Kurtosis
UAIHEC1	3.8396	1.13084	-0.886	0.215
UAIHEC2	3.7264	1.08262	-0.855	0.353
UAIHEC3	3.6698	0.92295	-0.476	0.446
UAIHEC4	4.066	1.0073	-1.16	1.07
UAIHEC5	3.7547	1.00296	-0.526	-0.02
UAIHEC6	3.5943	1.03995	-0.464	-0.184
UAIHEC7	3.717	0.98324	-0.443	-0.246
UAIHEC8	3.7547	0.97406	-0.495	-0.137
UAIHEC9	3.5755	0.97539	-0.373	-0.069
UAIHEC10	3.5189	0.91788	-0.019	-0.452
SA1	3.9623	0.84992	-0.591	0.346
SA2	3.8774	0.86962	-0.555	0.216
SA3	3.9906	0.86735	-0.874	1.273
SA4	3.8491	0.90283	-0.882	1.282
SA5	3.717	0.96367	-0.638	0.325
PCAI1	3.4906	0.98798	-0.275	-0.002
PCAI2	3.4811	0.90744	-0.255	0.288
PCAI3	3.434	0.94636	-0.287	0.226
PCAI4	3.3491	0.9466	-0.206	0.1
PCAI5	3.434	0.98579	-0.299	-0.331
CQAI1	3.7453	0.94679	-0.564	0.096
CQAI2	3.5094	0.94864	-0.369	0.023
CQAI3	3.6698	0.90208	-0.483	0.256
CQAI4	3.7736	0.91841	-0.659	0.751
CQAI5	3.783	0.98566	-0.887	0.78
PUAI1	3.3868	1.00067	-0.379	-0.063
PUAI2	3.4571	0.89902	-0.638	0.631
PUAI3	3.4906	0.85351	-0.579	0.754
PUAI4	3.6981	0.89623	-0.657	0.479
PUAI5	4	0.82808	-0.718	0.773
PUAI6	3.6792	0.91075	-0.703	0.737
PUAI7	3.8774	0.8586	-0.68	0.962

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUAI* Perceived Utility of Artificial Intelligence

demonstrated moderate to high levels of agreement, ranging from 3.3491 (PCAI4) to 4.066 (UAIHEC4), with standard deviations generally below 1.1, reflecting moderate variability [36]. These results indicate that the data are suitable for subsequent analyses, including PLS-SEM.

### 4.3 Measurement and structural model

In this study, all constructs such as Use of AI in Higher Education Curricula (UAIHEC), Satisfaction (SA), Perceived Credibility of AI Tools (PCAI), Content Quality of AI Tools (CQAI), and Perceived Utility of AI Tools (PUAI) were modelled as first-order reflective constructs, each measured directly through reflective indicators. The measurement model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4.0. Following Hair et al. [22], internal consistency reliability was confirmed through Cronbach's Alpha and Composite Reliability (CR), both exceeding 0.70. Convergent validity was supported by factor loadings above 0.70 and Average Variance Extracted (AVE) values above 0.50. Discriminant validity was confirmed through the Fornell-Larcker criterion, cross-loading analysis, and the Heterotrait-Monotrait (HTMT) ratio, with all values within acceptable thresholds. As such, no second-order constructs

were modelled in this study, and all constructs were treated as unidimensional reflective structures, aligned with their theoretical underpinnings.

Prior to applying the PLS-SEM technique, data normality was examined. The results indicated that skewness and kurtosis values ranged between 1.0 and  $-0.1$ , affirming the normal distribution of the data. Furthermore, the variance inflation factors (VIF) for UAIHEC, PUIAI, SA, CQAI, and PCAI were all below 5, confirming the absence of collinearity issues among the latent variables. Table 2 subsequently presents the measurement model, outlining indices related to reliability and convergent validity.

As presented in Table 3, all constructs demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.889 to 0.929 and composite reliability values ranging from 0.897 to 0.933. In terms of convergent validity, the AVE values for all variables exceeded the threshold of 0.5. Furthermore, all item factor loadings were above 0.70, indicating no concerns regarding convergent validity for the instruments utilised in this study.

Divergent validity was assessed using the HTMT ratio, Fornell–Larcker criterion, and cross-loadings. The results of the HTMT analysis for the variables are detailed in Table 3.

The results indicate that all HTMT values (Table 4) for the constructs and their dimensions are below the threshold of 0.90, providing preliminary evidence for the divergent validity of the instruments. Also, the assessment of divergent

**Table 3** Reliability and convergent validity of the instruments

Factors	items	Loading	CA	CR	AVE
UAIHEC	UAIHEC1	0.791	0.929	0.933	0.610
	UAIHEC2	0.712			
	UAIHEC3	0.773			
	UAIHEC4	0.831			
	UAIHEC5	0.848			
	UAIHEC6	0.786			
	UAIHEC7	0.797			
	UAIHEC8	0.761			
	UAIHEC9	0.764			
	UAIHEC10	0.737			
PUIAI	PUIAI1	0.784	0.919	0.923	0.674
	PUIAI2	0.825			
	PUIAI3	0.776			
	PUIAI4	0.835			
	PUIAI5	0.848			
	PUIAI6	0.848			
	PUIAI7	0.828			
SA	SA1	0.878	0.919	0.920	0.756
	SA2	0.888			
	SA3	0.862			
	SA4	0.855			
	SA5	0.865			
CQAI	CQAI1	0.812	0.889	0.897	0.692
	CQAI2	0.801			
	CQAI3	0.867			
	CQAI4	0.826			
	CQAI5	0.853			
PCAI	PCAI1	0.836	0.899	0.902	0.714
	PCAI2	0.903			
	PCAI3	0.899			
	PCAI4	0.747			
	PCAI5	0.830			

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUIAI* Perceived Utility of Artificial Intelligence, *CA* Cronbach Alpha, *CR* Composite Reliability, *AVE* Average Variance Extracted

**Table 4** Discriminant validity (HTMT Value)

	CQAI	PCAI	PUAI	SA	UAIHEC
CQAI					
PCAI	0.752				
PUAI	0.870	0.782			
SA	0.788	0.645	0.841		
UAIHEC	0.770	0.644	0.813	0.876	

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUAI* Perceived Utility of Artificial Intelligence

validity must take into account the Fornell–Larcker criterion. The outcomes of the Fornell–Larcker analysis are presented in Table 5. As per Hair [22], the square root of the AVE for each construct should exceed the highest correlation between that construct and any other construct within the model, therefore confirming divergent validity.

As shown in Table 5, all measured values meet the established criteria, further confirming the divergent validity of the instruments. Besides, the analysis of item cross-loadings indicates that the factor loadings within their respective constructs are consistently higher than those with other related constructs. This finding provides further evidence that there are no issues with divergent validity in the context of this study.

Cross-loading is identified when a factor's item-loading values on its respective construct are greater than its cross-loading on other constructs [23]. The values in bold in Table 6 indicate the highest loading for each item, confirming that items load more strongly on their intended constructs than on others. For example, CQAI1 has the highest loading value on its construct CQAI (0.812) compared to its cross-loadings on PCAI (0.489), PAUI (0.67), S (0.68), and UAIHEC (0.633). Similarly, PCAI2 loads the highest on PCAI (0.903) compared to its cross-loadings on CQAI (0.568), PAUI (0.597), S (0.521), and UAIHEC (0.52). These results demonstrate strong discriminant validity, as items consistently exhibit higher loadings on their respective constructs than on other constructs. This supports the robustness of the measurement model for subsequent structural equation modelling analyses.

According to Table 7, PAUI has a positive and significant effect on UAIHEC ( $\beta = 0.209$ ,  $t = 2.21$ ,  $p = 0.027 < 0.05$ ). Additionally, the confidence interval (0.038 to 0.401) does not include zero, further confirming the significance of this relationship. Therefore, H1 is supported. SA also exhibits a positive and significant impact on UAIHEC ( $\beta = 0.531$ ,  $t = 6.751$ ,  $p = 0.000 < 0.05$ ). The confidence interval (0.37 to 0.68) excludes zero, reinforcing the result. Hence, H2 is supported. For CQAI, the effect on UAIHEC is positive but not significant ( $\beta = 0.136$ ,  $t = 1.872$ ,  $p = 0.061 > 0.05$ ). The confidence interval (-0.019 to 0.276) includes zero, indicating no statistical significance. Thus, H3 is not supported. Similarly, PCAI shows a weak and non-significant effect on UAIHEC ( $\beta = 0.041$ ,  $t = 0.635$ ,  $p = 0.525 > 0.05$ ). The confidence interval (-0.074 to 0.162) includes zero, confirming the insignificance of this relationship. Consequently, H4 is not supported.

The  $R^2$  value represents the proportion of variance in endogenous latent variables that is explained by exogenous variables. According to Hair et al. [23],  $R^2 \geq 0.67$  indicates substantial predictive relevance,  $0.33 \leq R^2 < 0.67$  signifies moderate predictive relevance,  $0.19 \leq R^2 < 0.33$  denotes weak predictive relevance, and  $R^2 < 0.19$  indicates very weak or no predictive relevance. Based on these criteria, Fig. 1 demonstrates that the value for UAIHEC is 0.710. This indicates that 71.0% of the variance in UAIHEC is explained by PAUI, SA, CQAI, and PCAI within the model. Consequently, the variance of UAIHEC explained by these four factors demonstrates substantial predictive relevance.

**Table 5** Discriminant validity (Fornell–Larcker value)

	CQAI	PCAI	PUAI	SA	UAIHEC
CQAI	0.832				
PCAI	0.668	0.845			
PUAI	0.792	0.703	0.821		
SA	0.724	0.590	0.780	0.870	
UAIHEC	0.714	0.590	0.758	0.817	0.781

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUAI* Perceived Utility of Artificial Intelligence

**Table 6** Cross-loading

	CQAI	PCAI	PUAI	S	UAIHEC
CQAI1	0.812	0.489	0.67	0.68	0.633
CQAI2	0.801	0.627	0.59	0.47	0.487
CQAI3	0.867	0.625	0.657	0.577	0.564
CQAI4	0.826	0.532	0.628	0.554	0.554
CQAI5	0.853	0.532	0.726	0.687	0.692
PCAI1	0.621	0.836	0.641	0.582	0.546
PCAI2	0.568	0.903	0.597	0.521	0.52
PCAI3	0.587	0.899	0.62	0.513	0.489
PCAI4	0.496	0.747	0.535	0.442	0.464
PCAI5	0.535	0.83	0.568	0.42	0.465
PUAI1	0.662	0.724	0.784	0.589	0.543
PUAI2	0.614	0.561	0.825	0.55	0.576
PUAI3	0.637	0.665	0.776	0.514	0.552
PUAI4	0.64	0.541	0.835	0.655	0.656
PUAI5	0.696	0.487	0.848	0.751	0.671
PUAI6	0.632	0.587	0.848	0.709	0.668
PUAI7	0.674	0.525	0.828	0.679	0.667
SA1	0.584	0.488	0.642	0.878	0.691
SA2	0.681	0.486	0.662	0.888	0.72
SA3	0.637	0.509	0.696	0.862	0.695
SA4	0.607	0.475	0.674	0.855	0.7
SA5	0.638	0.603	0.714	0.865	0.745
UAIHEC1	0.601	0.495	0.632	0.702	0.791
UAIHEC10	0.455	0.468	0.522	0.537	0.737
UAIHEC2	0.494	0.351	0.549	0.584	0.712
UAIHEC3	0.504	0.473	0.563	0.555	0.773
UAIHEC4	0.605	0.463	0.62	0.752	0.831
UAIHEC5	0.64	0.51	0.672	0.737	0.848
UAIHEC6	0.553	0.47	0.597	0.628	0.786
UAIHEC7	0.62	0.486	0.637	0.694	0.797
UAIHEC8	0.529	0.393	0.55	0.566	0.761
UAIHEC9	0.532	0.494	0.55	0.566	0.764

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUAI* Perceived Utility of Artificial Intelligence

**Table 7** Hypotheses testing

	Path coefficient	T statistics	P values	CI	Results
H1: PUA1 → UAIHEC	0.209	2.21	0.027	(0.038, 0.401)	Supported
H2: SA → UAIHEC	0.531	6.751	0.000	(0.37, 0.68)	Supported
H3: CQAI → UAIHEC	0.136	1.872	0.061	(-0.019, 0.276)	Not supported
H4: PCAI → UAIHEC	0.041	0.635	0.525	(-0.074, 0.162)	Not supported

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUAI* Perceived Utility of Artificial Intelligence

To gain deeper insights into which predictor has the most substantial impact on UAIHEC, it is essential to examine the values. The  $f^2$  effect size of each predictor represents its unique contribution to the  $R^2$  value of the dependent variable when included in the model, as compared to when it is excluded. According to Hair et al. [23],  $f^2 \leq 0.02$  indicates a small effect size,  $0.15 \leq f^2 \leq 0.02$  indicates a medium effect size, and  $f^2 \geq 0.35$  indicates a large effect size. Table 8 presents the  $f^2$  values of each specific predictor on UAIHEC, highlighting their respective contributions to the model.



**Fig. 1** Structural model. *UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUI* Perceived Utility of Artificial Intelligence

**Table 8** Predictive relevance of  $f^2$

	UAIHEC
CQAI	0.022
PCAI	0.002
PUI	0.037
SA	0.361

*UAIHEC* Use of Artificial Intelligence in Higher Education Curricula, *SA* Satisfaction, *PCAI* Perceived Credibility of Artificial Intelligence, *CQAI* Content Quality of Artificial Intelligence, *PUI* Perceived Utility of Artificial Intelligence

Table 8 highlights the  $f^2$  effect sizes for the predictors on UAIHEC, thus showing their contributions to the model’s explanatory power. SA emerges as the most significant predictor, with an  $f^2$  value of 0.361. This indicates a large effect size and underscores its substantial influence on UAIHEC. PUI demonstrates a medium effect size, with an  $f^2$  value of 0.037. This suggests

a moderate yet meaningful contribution to the dependent variable. Similarly, CQAI has a medium effect size of 0.022 and reflects a limited but notable impact. In contrast, PCAI has an  $f^2$  value of 0.002, signifying a small effect size and minimal influence on UAIHEC. These findings emphasise the dominant role of SA in predicting UAIHEC, while the contributions of PUAI and CQAI are moderate, and PCAI's impact is negligible.

The predictive relevance of the model was evaluated using the Blindfolding Technique in SmartPLS 4, following the guidelines of Hair et al. [22], to determine the Q2 value. The Q2 value reflects the ability of a latent variable to predict the associated dependent variable within the model. A high Q2 value indicates strong predictive relevance of the latent variable for the dependent variable, whereas a low Q2 value suggests limited predictive capacity. As shown in Table 9, the Q2 value for UAIHEC exceeds 0 (0.691), confirming the predictive validity of the endogenous construct in the model.

## 5 Discussion

The findings from this study provide crucial insights into students' perceptions and engagement with AI tools in higher education, emphasising the roles of satisfaction, perceived credibility, content quality, and perceived utility. These results contribute to the broader discourse on AI adoption by reaffirming and extending prior research, highlighting a nuanced interplay between these factors and their impact on students' willingness to embrace AI in academic settings. This aligns with prior research by Dash et al. [16], which emphasized that self-efficacy, interaction, and content quality are critical determinants of user satisfaction and engagement in e-learning settings, highlighting the importance of addressing these factors for successful AI adoption in educational environments [16].

The study confirms that AI tools offer personalized learning pathways and improve content delivery efficiency, yet their impact depends heavily on how well they are integrated into pedagogical frameworks. This is consistent with findings by Rapanta et al. [52], who stressed the need for a balanced approach between technology and pedagogy for meaningful learning experiences [52]. The variance explained in this study ( $R^2 = 0.710$ ) highlights the strong combined influence of the identified predictors in which perceived utility, satisfaction, content quality, and perceived credibility influenced students' engagement with AI tools. This high variance suggests a complex interplay between these factors, as demonstrated by Bond et al. [13], who noted that technology adoption is rarely influenced by a single predictor, but rather a combination of factors influencing behavioural, affective, and cognitive engagement [13].

Perceived utility of AI (PUAI) emerged as a significant predictor of students' engagement with AI tools, showcasing its central role in determining technology adoption in educational settings. This is consistent with the Technology Acceptance Model (TAM) as discussed by Lijie et al. [31], which identifies perceived usefulness as a critical determinant of users' intention to use technology. The findings align with Abu Talib et al. [2], who highlighted that perceived utility drives technology adoption, particularly when it enhances performance and efficiency [2]. The study revealed that students perceive AI tools as useful primarily due to their ability to automate routine tasks, enhance content delivery, and adapt learning experiences to individual needs. However, the moderate effect size of PU in this study highlights its partial role in influencing AI adoption, suggesting that other factors such as emotional and experiential dimensions are equally important [16, 63].

To enhance AI's perceived utility, institutions must demonstrate its real-world relevance by integrating practical features, such as AI-powered career guidance or subject-specific simulations, that directly address students' academic and professional aspirations [55]. This is supported by Alwi and Ahmad Khan [9], who found that perceived ease of use (PEOU) and perceived usefulness (PU) significantly mediate technology readiness and decision-making in AI adoption among students.

Satisfaction (SA) was the strongest influence on the use of AI in higher education curricula, emphasizing its pivotal role in fostering engagement. This finding aligns with the Expectation-Confirmation Model (ECM), which posits that satisfaction arises when users' expectations are met or exceeded by their experiences [47]. Dash et al. [16] further emphasized that user satisfaction is a key driver of e-learning success, influencing user intention and long-term engagement [16]. In educational contexts, satisfaction with AI tools is closely tied to their reliability, ease of use, and alignment with students' learning objectives. For example, AI platforms that deliver timely feedback, enable seamless navigation, and adapt dynamically to learners' needs are more likely to garner positive responses. These findings align with Zou et al. [70], who emphasize that addressing technical challenges and providing a positive user experience are essential to fostering satisfaction and engagement with AI tools.

**Table 9** Predictive relevance of  $Q^2$

	$Q^2_{\text{predict}}$
UAIHEC	0.691

Contrary to expectations, the content quality of AI (CQAI) did not significantly impact students' use of AI in higher education curricula. This finding deviates from prior research. For example, Almufarreh [7] emphasizes content quality as a cornerstone of effective digital learning tools. A plausible explanation for this result is that students might take content quality for granted, assuming it to be a baseline feature of any educational tool. Consequently, its influence might be overshadowed by more dynamic factors such as usability or perceived utility [13, 16]. Future research should explore how specific dimensions of content quality, such as contextual relevance, depth, and adaptability, might impact students' perceptions of AI tools. For example, AI platforms that tailor content to regional or cultural contexts might resonate more effectively with diverse student demographics [55, 69].

Interestingly, perceived credibility AI (PCAI) had no significant influence on students' engagement with AI in higher education curricula, contradicting established literature that positions trust and credibility as fundamental to technology adoption [55]. This finding may stem from students' limited understanding of AI technologies, making it challenging to critically evaluate the credibility of AI-generated content. This aligns with Almufarreh [7], who suggested that credibility concerns are secondary to immediate functionality for most students. Institutions should prioritize transparency and accountability in AI systems by providing accessible explanations of AI processes, such as data sourcing and algorithmic decision-making, to foster greater trust in AI-generated outputs [6]. Additionally, Dash et al. [16] emphasized that incorporating mechanisms for verifying the credibility of AI outputs, such as citations for AI-generated content or peer-reviewed validation, could further enhance students' confidence in these tools.

Lastly, a key theoretical contribution of this study is its reinforcement of the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM). Specifically, perceived utility (PUAI) emerged as a critical determinant for AI adoption, supporting Lijie et al. [31] and Abu Talib et al. [2], who found that perceived usefulness significantly predicts user intention. However, the findings of the present study extend TAM by demonstrating that perceived utility alone is insufficient to drive AI adoption, as emotional and experiential factors also play a substantial role [63]. This aligns with Bond et al. [13], who emphasised that technology adoption is a complex process influenced by cognitive, affective, and behavioural engagement. Therefore, institutions must enhance AI's perceived utility by incorporating features that address both academic and professional aspirations, such as AI-powered career guidance or adaptive learning models [55].

Overall, this study contributes to the body of knowledge by refining our understanding of AI adoption in educational settings. By demonstrating the complex interplay between perceived utility, satisfaction, content quality, and credibility, this research extends existing theoretical frameworks, offering a more comprehensive view of student engagement with AI. These insights have direct implications for educators and policymakers seeking to optimize AI integration in curricula, ensuring that AI tools are not only functional but also engaging and trustworthy. Hence, future studies should further examine how demographic and contextual factors mediate these relationships, enabling a more tailored approach to AI implementation in higher education.

## 6 Conclusion

This study emphasises the importance of AI adoption in higher education (HE), particularly within the Malaysian context. The study recognizes that student perceptions are influenced by a dynamic interplay of satisfaction, perceived utility, content quality and credibility. While satisfaction and perceived utility of AI emerged as the strongest predictors of the use of AI in Malaysian higher education curricula, this study highlights the need for continuous refinement of AI tools to address students' evolving expectations and the unique characteristics of Malaysian HE. Institutions in Malaysia should not only focus on the technical features of AI systems but also invest in training programs to elevate both student and faculty competency in using these technologies effectively, keeping in mind the diverse linguistic, cultural, and socio-economic contexts of Malaysian learners.

Furthermore, integrating AI into Malaysian pedagogical frameworks requires addressing potential ethical and equity concerns specific to the country. Ensuring that AI tools are accessible and inclusive is vital to prevent exacerbating existing disparities between urban and rural education settings and between public and private institutions. Further, Malaysian institutions should establish robust feedback mechanisms to gather real-time insights from students and educators, enabling iterative improvements to AI systems. Such participatory approaches can foster a sense of ownership, collaboration, and alignment with the nation's educational aspirations outline in Malaysia Education Blueprint.

Last but not least, the study also highlights the necessity of blending AI with human judgement to preserve the cultural and empathetic aspects of education unique to Malaysia's multicultural society. While AI streamlines learning

processes, human oversight remains critical to ensure the quality, relevance, and ethical use of AI-generated content in line with Malaysian values. Hence, expanding research to include the perspectives of Malaysian educators, policymakers, and administrators could provide a more comprehensive understanding of the challenges and opportunities associated with AI integration in the country. Finally, cross-cultural and interdisciplinary studies within Southeast Asia and beyond could shed light on how contextual factors specific to Malaysia, such as language diversity, infrastructure gaps, and government policies, inadvertently shape AI adoption. This would offer valuable insights into the global education system while positioning Malaysia as an innovative, inclusive education leader.

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**Data availability** The datasets generated during and/or analysed during the current study are not publicly available due to the fact that the datasets used in this study were provided by a collaborating institution and contain sensitive information with usage restrictions. However, they are available from the corresponding author upon reasonable request.

## Declarations

**Ethics approval and consent to participate** This study was conducted in accordance with ethical guidelines and regulations established by the University of Malaya Research Ethics Committee (UMREC) at the University of Malaya. The data was collected from the participants after obtaining ethical approval from the UMREC at the University of Malaya, identified by the reference number UM.TNC2/UMREC\_2261. In addition, the participants also approved the informed consent form for participating in the self-reported survey.

**Competing interests** The authors declare no competing interests.

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## Appendix: Items retained after CFA

Factor	Item	Description
UAIHEC	UAIHEC1	Artificial intelligence is relevant to my everyday life in higher education curricula
	UAIHEC2	I am curious about discovering new AI technologies in higher education curricula
	UAIHEC3	I am confident I will perform well on AI learning tools in higher education curricula
	UAIHEC4	I will continue to use AI learning tools in the future
	UAIHEC5	I will keep myself updated with the latest AI learning tools in higher education curricula
	UAIHEC6	I often try to recommend and explain AI learning tools to my classmates or friends
	UAIHEC7	I try to work with my classmates to complete tasks and projects using AI learning tools
	UAIHEC8	I know how to use AI learning tools (e.g., Siri, chatbot)
	UAIHEC9	I can evaluate AI learning tools for different situations
	UAIHEC10	I can compare the differences between AI learning tools
SA	SA1	The use of AI tools for education greatly enhances my learning
	SA2	The practice of reviewing content and material for education enhances my learning
	SA3	It is helpful to be able to contact the AI tools
	SA4	AI tools greatly enhanced my ability to learn
	SA5	The information obtained from AI tools is valuable
PCAI	PCAI1	The content and material generated and provided by AI tools in education are believable
	PCAI2	The content and material generated and provided by AI tools in education are accurate
	PCAI3	The content and material generated and provided by AI tools in education are trustworthy
	PCAI4	The content and material generated and provided by AI tools in education are from any bias
	PCAI5	The content and material generated and provided by AI tools in education are complete
CQAI	CQAI1	The content generated by the AI tools is easy to understand
	CQAI2	The content generated by the AI tools is new
	CQAI3	The content generated by the AI tool is refreshing
	CQAI4	The content generated by the AI tools is popular
	CQAI5	The content generated by the AI tools is relevant for users
PUAI	PUAI1	I am confident in the quality and accuracy of AI tools
	PUAI2	In AI tools, I received what I paid for
	PUAI3	The educational materials provided by AI tools were adequate
	PUAI4	Having AI tools gave me more control over my learning goals
	PUAI5	I learned something by using AI tools that I did not know before
	PUAI6	The information I received has influenced how I will manage my educational goals in the future
	PUAI7	What I learned can help reduce my chances of failing exams

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