

Predicting Factors Influencing Behavioural Intention and Actual Use Behaviour of Artificial Intelligence (AI): Extending UTAUT2 Model with Personal Innovativeness, Perceived Trust and Perceived Risk

Siti Fairus Fuzi^{1*}, Nurul Emyza Zahidi¹, Bushra Abdul Halim², Siti Nursyahira Zainudin³, Siti Ramizah Jama⁴, Nordinah Jusoh⁵, Wan Hartini Wan Hassan⁶

Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), Kampus Alor Gajah, Km 26 Jalan Lendu, 78000 Alor Gajah, Melaka, Malaysia

*Corresponding Author

DOI: <https://doi.org/10.47772/IJRISS.2026.100700545>

Received: 22 July 2026; Accepted: 27 July 2026; Published: 07 August 2026

ABSTRACT

This research examined the factors influencing university students' behavioural intention to use artificial intelligence (AI) and its actual use behaviour using UTAUT2 model and extending it using personal innovativeness, perceived trust, and perceived risk. A cross-sectional study was employed and targeting diploma and undergraduate students from six prominent public universities in Malaysia. The survey evaluated the predictors of UTAUT2 model including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit and introduced the variables of personal innovativeness, perceived trust, and perceived risk into the original UTAUT2 structure. Data were gathered from 301 respondents, firstly, assessing the influences of UTAUT2 predictor variables on the behavioural intention to use AI. Secondly, the impacts of UTAUT2 predictor variables along with students' behavioural intention on AI actual use behaviour were evaluated. Lastly, the mediating effect of behavioural intention to use AI on the relationships between each predictor with AI actual use behaviour was investigated. Using hierarchical multiple regression analysis, the results indicated that performance expectancy, facilitating conditions, hedonic motivation, price value, and perceived trust significantly and positively while perceived risk negatively impacted behavioural intention to use AI, suggesting the robustness of the original UTAUT2 structure. Effort expectancy and social influence did not show a significant impact. Performance expectancy, habit, personal innovativeness, perceived trust, and behavioural intention to use AI are revealed to significantly and positively affecting AI actual use behaviour while price value and perceived risk are evident to have negative influences on the actual use. Effort expectancy, social influence, facilitating conditions, and hedonic motivation are shown insignificant with AI actual use behaviour. Results of mediation analyses suggested that students' belief in greater performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, perceived trust, and reduced perceived risk will foster strong behavioural intentions to use AI, which ultimately influences their decision to actually use AI technologies. This study contributes to the understanding of the interplay between various factors in behavioural intention to use AI and AI actual use as well as offers strategic insights for the successful implementation of AI systems in Malaysian universities.

Keywords: Artificial intelligence, UTAUT2 model, behavioural intention to use AI, actual use of AI, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, perceived trust, and perceived risk

INTRODUCTION

The rapid technological advancement of artificial intelligence (AI) globally is transforming various sectors, including the educational sector (Vieriu & Petrea, 2025). In education, this transformative technology is steering in a new era of collaborative, data-driven, and globally relevant pedagogy (Chatterjee & Bhattacharjee, 2020). The integration of AI in education has transformed teaching and learning activities with rapid usage of AI among

academicians and students in assisting their academic tasks. According to academics, chatbots, specifically ChatGPT have a lot of uses in education, and its potential to transform teaching and learning is greatly foreseen (Oravec, 2023). ChatGPT is thought to help students manage their academic tasks more efficiently and provide them with more individualized instruction (W. Wu et al., 2022). Regarding information technology acceptance, (Venkatesh et al., 2003) formulated four variables: performance expectancy, effort expectancy, social influence, and facilitating conditions into a unified model, called the Unified Theory of Acceptance and Use of Technology (UTAUT) and it was then confirmed with 70 percent of the variables explaining behavioural intention which in turn positively predicted the usage behaviour. Later, (Venkatesh et al., 2012) refined their original UTAUT model into UTAUT2 model by incorporating three more variables: hedonic motivation, price value, and habit which influenced behavioural intention. The UTAUT and UTAUT2 models have been employed in a wide range of studies exploring an array of educational technologies, including, e-learning systems [(Abbad, 2021), (Zacharis & Nikolopoulou, 2022)], mobile devices [(Chao, 2019), (Ikhsan et al., 2021), (Abdallah et al., n.d.), (Nguyen & Teng, 2022)], and Learning Management Systems (Raza et al., 2021).

This present study will integrate three more predictors; personal innovativeness [(Palacios-Marqués et al., n.d.), (“Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students,” 2023)], perceived trust [(Palacios-Marqués et al., n.d.), (“Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students,” 2023), (Emon et al., 2023), (Su et al., 2025)], and perceived risk [(Chatterjee & Bhattacharjee, 2020), (Palacios-Marqués et al., n.d.), (Acosta-Enriquez et al., 2024), (Su et al., 2025)] into the original UTAUT2 model. Many previous research [(Strzelecki, 2024), (Palacios-Marqués et al., n.d.), (Cortez et al., 2024), (Grassini et al., 2024)] had shown independently significant positive impacts of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, and perceived trust while perceived risk was revealed to have negative influence on behavioural intention to use AI.

Many past studies had focused the effects of the predictors (either four predictors of UTAUT model or seven predictors of UTAUT2 model) on behavioural intention to use AI, however, limitedly showed the impacts of the predictors on AI actual use behaviour. Additionally, very few research studied on mediating effect of behavioural intention to use AI on the relationships between each of the predictors with AI actual use behaviour. Therefore, to fill in the gap of previous research, the goal of this study is to provide substantial insights into the UTAUT2 predictors plus the three newly added predictors (personal innovativeness, perceived trust, perceived risk) that influence behavioural intention to use AI and to investigate the impact of UTAUT2 predictors plus the three newly added predictors together with behavioural intention to use AI on AI actual use behaviour. In addition, this present study will also examine and provide valuable insights into the mediating role of behaviour intention to use AI in the AI actual use behaviour.

LITERATURE REVIEW

Earlier study by (Venkatesh et al., 2003) theorized unified theory of acceptance and use of technology (UTAUT) model consisting of four constructs that played a significant role as determinants of user acceptance and user usage of technology; performance expectancy, effort expectancy, social influence, and facilitating conditions. However, in a later study of (Venkatesh et al., 2012)(Venkatesh et al., 2012), they proposed to incorporate other three constructs, namely, hedonic motivation, price value, and habit in UTAUT and named it as UTAUT2. Later, (Patil et al., 2020) extended the UTAUT model with consumer related constructs such as anxiety, personal innovativeness, and perceived trust as determinants of user acceptance and user usage of technology, while (Su et al., 2025) introduced perceived trust and perceived risk into the UTAUT model. The current study attempts to establish the associations among all UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk in the proposed model and their context in examining behavioural intention and actual use behaviour of AI-based tools among Malaysian university students in their daily lives as well as for learning purposes. Through comprehension of these constructs, higher education institutions can plan strategies to encourage the adoption of AI and guarantee its beneficial integration into educational settings.

Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance [(Venkatesh et al., 2003), (Venkatesh et al., 2012)]. Performance

expectancy can also be referred to the benefits that users associate with the adoption of technology or system in higher education [(Hanim Mohsin et al., 2024), (Polyportis & Pahos, 2025)]. This study identifies it as students' belief that AI-enabled tools will support them to achieve or perform their academic tasks. Recent literature on AI, [(Chao, 2019), (Strzelecki, 2024), (Hanim Mohsin et al., 2024), (Polyportis & Pahos, 2025)] emphasized the impact of performance expectancy in determining students' behavioural intention to use technologies in higher education. Studies by [(Patil et al., 2020), (Cao et al., 2021)], stressed on the significant positive association of performance expectancy and AI use. Students are more likely to use AI if they believe it will help them to perform successfully in their academic tasks.

Effort expectancy is the degree of ease associated with individual's use of technology [(Venkatesh et al., 2003), (Venkatesh et al., 2012)]. According to Davis (1989), user convenience has a positive influence on the use of information technology. For this research, effort expectancy reflects the perceived ease of use of incorporating AI technology in achieving students' learning outcomes. This means an individual student believes that he or she can easily understand and operate the AI system or technology for a particular academic task when using it. Individuals are more likely to use the AI technologies into their work processes if the technologies are designed to be user-friendly, intuitive, understandable, and require minimal effort to operate (Emon et al., 2023). In the context of AI, if the AI technologies require minimal effort to learn and operate, then individuals are more likely to express a positive behavioural intention to use them. On the other hand, if individuals perceive AI technology as challenging and adversely affecting the intention to use, thus reflecting it as a significant barrier to AI engagement (Krishnanraw & Ismail, 2025). Contrarily, (Raza et al., 2021) revealed a positive influence of effort expectancy on the behavioural intention to adopt Learning Management System. Therefore, it is a crucial consideration in the design and implementation of AI technologies by considering the minimal effort expectancy as lower perceived effort contributes to higher user acceptance.

Social influence is defined as the degree to which the consumer perceives that family, peers, friends, and colleagues are important in their life who believe that they should use a specific technology [(Venkatesh et al., 2003), (Venkatesh et al., 2012)]. Based on the literature, (Räisänen et al., 2020) connected social influence to peer-learning, social learning, and students' informal activity to support each other in higher education. ("Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students," 2023) revealed that students would accept AI tools based on recommendations from peers whereby they benefited from their peers when making decisions with technologies in education. (Raffaghelli et al., 2022) noted that social influence is a good predictor of technology acceptance. According to (Venkatesh & Davis, 2000), social influence is significant in mandatory context rather than voluntary context. In mandatory settings, social influence appears to be significant in the early stages of technology acceptance and subsequently with sustained usage of technology, the role of social influence seems to be eroded over time (Venkatesh & Davis, 2000).

Facilitating conditions refer to the extent to which an individual perceives the presence of an organizational and technical infrastructure, support systems, and resources that support the behaviour of utilizing a system [(Venkatesh et al., 2003), (Venkatesh et al., 2012)]. This indicates if the operational infrastructure exists and facilitates to use the AI system, the behavioural intention to adopt the AI system will increase (Oliveira et al., 2016). Some factors that contribute to a conducive environment for AI adoption include adequate funding, technological infrastructure, IT support, access to training and development programs, and institutional policies supporting AI integration (Hanim Mohsin et al., 2024). In the Learning Management System, (Raza et al., 2021) demonstrated an insignificant positive relationship between facilitating conditions with behavioural intention of the system suggesting that the infrastructure and availability of timely assistance did not significantly impact students' intention to use the system for completing their coursework. In social development organizations, the study by (Jain et al., 2022) discovered that employees received organizational and technical support for adopting and using online technologies powered by AI for their work implying that people are more likely to adopt AI in organizations that provide a supportive environment like facilities, resources, and training, where peers, superiors, and subordinates adopt the same technology. Over time, social influence and facilitating conditions would change eventually due to ongoing social interactions and pedagogical activity (Venkatesh & Davis, 2000).

Hedonic motivation is defined as the fun or pleasure derived from using a technology and it has been shown to play an important role in determining technology acceptance and use (Venkatesh et al., 2012). The finding of (“Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students,” 2023) indicated that the psychological need of students has a significant direct effect on AI acceptance suggesting the intrinsic motivation and inner satisfaction of an individual during learning is uppermost to the kind of technology to use. This implies that students with strong hedonic motivation in education are more likely to have a greater acceptance of AI than students with hedonic motivation.

(Venkatesh et al., 2012) defined price value as the consumer's cognitive trade-off between the perceived benefits of the technologies and the monetary cost of using them. (Strzelecki, 2024) refers price value to the cost students bear when purchasing access to the online services used for learning. The perceived benefits of using a technology are greater when the price value is more, and the perceived monetary cost is less and therefore, such price value has a positive impact on intention (Venkatesh et al., 2012).

Habit is another factor that should be considered impacting behavior intention [(Hirt & Cheung, 2007), (Venkatesh et al., 2012), (Cabrera-Sánchez et al., 2021)]. (Hirt & Cheung, 2007) defined habit as the extent to which people tend to perform behaviours automatically because of learning. (Venkatesh et al., 2012) has integrated habit into their UTAUT2 model. Habit is also referred as the accumulation of prior experiences (Lin et al., 2023). (Saudjhana & Herman, 2023) found that habits along with factors of effort expectancy, social influence, and facilitating conditions simultaneously can effectively generate behavioural intention to adopt digital bank mobile application among housewives. (Venkatesh et al., 2012) also showed that the effects of habit on behavioural intention and use behaviour were stronger for older men and with high levels of technology experience.

(Rogers, 1995) refers *personal innovativeness* to an idea, practice, or object that is perceived as new by an individual. According to (Rogers, 1995), the perceived newness of the idea for the individual determines his or her reaction to it and if the idea seems new to the individual, it is then called an innovation. Newness in an innovation need not just involve new knowledge but the innovation may have been known by an individual for some time but not yet developed a favorable or unfavorable attitude toward it, nor have adopted or rejected it and it may be expressed in terms of knowledge, persuasion, or a decision to adopt (Rogers, 1995). [(Farooq et al., 2017), (Patil et al., 2020), (“Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students,” 2023)] had acknowledged that personal innovativeness as important factor that impact technology adoption and usage suggesting that personality traits, such as personal innovativeness, play a significant role in technology adoption in the domain of information technology.

(Patil et al., 2020) defined *perceived trust* as the willingness of an individual to rely on another party in a situation involving risk. A study by (Toreini et al., 2019) indicates that users are more likely to adopt a system if they have a high level of trust in the system’s reliability. According to (Palacios-Marqués et al., n.d.), users often feel uncertain when the technology is first emerging, however, this uncertainty can be eliminated, when the users have a pre-existing feeling of trust toward a specific technology. The results of the study (Su et al., 2025) suggest that a higher degree of trust in AI health assistant systems correlates with increased expectations regarding their performance and effort requirements, thereby enhancing users’ inclination to utilize the systems while simultaneously diminishing their perceived risks associated with usage.

(Featherman & Pavlou, 2003) defined *perceived risk* as the potential for loss in the pursuit of a desired outcome of using a technology. According to (Chatterjee & Bhattacharjee, 2020), perceived risk is a blending of behavioural insecurity and environmental insecurity. If perceived risk was reduced, it impacted significantly on the attitude of the users (Susanto & Goodwin, n.d.) which in turn influencing behavioural intention to use (Chatterjee & Bhattacharjee, 2020). Thus, perceived risks are associated with the negative feeling of the users of AI in higher education (Chatterjee & Bhattacharjee, 2020). Perceived risk may affect students’ concerns about ethical issues, privacy concerns, and copyright problems [(Tao et al., 2023), (J. Wu et al., 2023)] which constitute cognitive risk (W. Li, 2025). Perceived risk also involves impacting users’ emotional experiences (Lang, 2018). These emotional experiences affect individuals’ attitudes and emotions (Strohmaier et al., 2019), making them

more resistant to adopting the technology (W. Li, 2025). In the present study, perceived risk is referred to the likelihood of a student suffering a loss in behavioural intention to use AI and actual using AI technologies.

Behavioural intention refers to the tendency of individuals to adopt a specific technology for carrying out various tasks demonstrating their willingness and effort to perform a particular behaviour [(Patil et al., 2020), (Raza et al., 2021)]. According to Emon et al. (2023), behavioural intentions are influenced by several factors, including attitude towards AI, effort expectancy, facilitating conditions, performance expectancy, social influence, and perceived trust. Among these predictors, facilitating conditions demonstrate the strongest positive influence on behavioural intentions, followed by performance expectancy, perceived trust, attitude towards AI, and social influence. In the study, Emon et al. (2023) found that as effort expectancy and hedonic motivation increased, there was a decrease in behavioural intention implying there was a challenge in utilizing ChatGPT which might be due to difficulties in formulating appropriate commands for desired outputs which was not fun that resulting in reduced levels of adoption and usage. However, (Biloš & Budimir, 2024) revealed effort expectancy, facilitating conditions, and price value as insignificant predictors of students' behavioural intentions to use ChatGPT. The insignificance influence of effort expectancy on behavioural intention may be due to the increasing familiarity among the young people, with the internet and digital technologies (Merhi et al., 2019). Additionally, according to Emon et al. (2023), behavioural intentions strongly predict the actual use of ChatGPT, highlighting their pivotal role in driving the technology's adoption and utilization.

Actual use behavior refers to the extent to which users actually use a technology for a specific task or purpose and it aims to explain user's technology acceptance and usage behaviour (Venkatesh et al., 2012). Studies like [(Venkatesh et al., 2012), (Strzelecki, 2024), (Strzelecki, 2025), (Grassini et al., 2024)] measured use behaviour as a single measure (never, once a month, several times a month, once a week, several times a week, once a day, several times a day). Prior research has argued that behavioural intention is a good substitute for use behaviour. Many prior research did not study for actual use behaviour which might be due to a lack of consistent measurement items to collect responses on this construct and it had been argued that behavioural intention was a good substitute for use behaviour (Patil et al., 2020). Studies like [(Venkatesh et al., 2012), (Grassini et al., 2024), (Strzelecki, 2024), (Faraon et al., 2025), (Moradi, 2025), (Cabero-Almenara et al., 2025)] used a single item measure on a 7-options scale ranging from never to several times a day to measure use behaviour while studies such as [(Patil et al., 2020), (Romero-Rodríguez et al., 2023), (Budhathoki et al., 2024), (Rashid, 2025)] used a 5-Likert scale (1 – strongly disagree to 5 – strongly agree) or 7-Likert scale (1 – strongly disagree to 7 – strongly disagree) to capture the varying levels of use behaviour.

Earlier study of (Venkatesh et al., 2003) using UTAUT model with constructs performance expectancy, effort expectancy, social influence, and facilitating conditions, found that the model could explain almost 70% of variance in behavioural intention. Many researchers used UTAUT model with inclusion of other new constructs like perceived trust and perceived risk (Su et al., 2025), attitude and perceived risk (Chatterjee & Bhattacharjee, 2020), while [personal innovativeness, anxiety, trust, and attitude (Patil et al., 2020)]. The results of (Su et al., 2025), indicated that performance expectancy, effort expectancy, and social influence significantly positively affected behavioural intention, while facilitating conditions did not show a significant impact, while perceived risk negatively affected behavioural intention. According to [(Chatterjee & Bhattacharjee, 2020), (Su et al., 2025)], the original UTAUT model by (Venkatesh et al., 2003) is considered robust and helpful to interpret behavioural intention of users to accept a modern technology like AI.

Likewise, many researchers also used UTAUT2 model (Venkatesh et al., 2012) to demonstrate relationship between UTAUT2 constructs with behavioural intention to use for a specific technology. For example, (Romero-Rodríguez et al., 2023) studied the impacts of UTAUT2 constructs on behavioural intention to use ChatGPT among Spanish university students aged 18 – 64 years and found that performance expectancy, hedonic motivation, price value, and habit were influential while effort expectancy, social influence, and facilitating conditions did not influence behavioural intention to use ChatGPT. The findings of (Grassini et al., 2024) revealed performance expectancy emerged as the construct with the biggest impact on behavioural intention to use ChatGPT, followed by habit, while effort expectancy, social influence, facilitating conditions, and hedonic motivation were insignificant factors of behavioural intention to use ChatGPT. Some researchers extended UTAUT2 model by including some other factors or modifying it by not using some of UTAUT2 constructs but

included some other variables that could fit their research contexts. Findings of (Biloš & Budimir, 2024) revealed that performance expectancy, social influence, hedonic motivation, habit, and personal innovativeness significantly influenced the behavioural intention to use ChatGPT, while effort expectancy, facilitating conditions, and price value did not exhibit a significant impact. Emon et al. (2023) highlighted the significance of strengthening behavioural intentions, emphasizing performance benefits, building trust, and creating facilitating conditions to promote adoption and utilization of ChatGPT among professionals in Bangladesh. A study by (W. Li, 2025) showed perceived risk demonstrated a negative impact on the intention to use AI-Generated Content tools among design students and practitioners.

(Palacios-Marqués et al., n.d.) showed habit, trust, and personal innovativeness have positive significant impacts on the adoption of virtual assistants, however, performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, and perceived privacy risk were shown as insignificant factors in the users' intention to adopt virtual assistants. A study by ("Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students," 2023) demonstrated a positive and significant effect of perceived usefulness, effort expectancy, social influence, innovation characteristics, and psychological needs of students on AI acceptance in education. (Strzelecki, 2024) revealed performance expectancy, effort expectancy, social influence, hedonic motivation, price value, habit, and personal innovativeness, but not facilitating conditions, had positive influences on behavioural intention to use ChatGPT and revealed that personal innovativeness as one of the factors driving students' behavioural intention to use ChatGPT in higher education. Personal innovativeness has positive influence on behavioural intention, and it strengthens the belief that innovative people are capable of remaining optimistic and positive when confronted with new technology [("Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students," 2023), (Palacios-Marqués et al., n.d.)]. (Faraon et al., 2025) compared UTAUT2 factors influencing ChatGPT adoption among higher education students in five Nordic countries (Sweden, Finland, Denmark, Norway, and Iceland) and the USA, found that one of the factors, personal innovativeness was a predictor of behavioural intention in the USA sample but not in Nordic sample. Many research had shown negative influence of perceived risk and positive impact of trust on behavioural intention to use a technology. (Acosta-Enriquez et al., 2024) showed a significant negative influence of perceived risk on intention to use ChatGPT. (Chatterjee & Bhattacharjee, 2020) found a significant negative impact of perceived risk on attitude, which in turn, positively impacted the behavioural intention to use AI in higher education. (Su et al., 2025) expanded the UTAUT model by including perceived risk and perceived trust, found a significant negative impact of perceived risk and a significant positive influence of perceived trust on AI health assistants. However, [(Swathi et al., 2025), (Yakubu et al., 2025)] showed insignificant influence of perceived risk on behavioural intention to use AI. With regard to trust, Emon et al. (2023) found a significant positive influence of trust on behavioural intention to use ChatGPT. (Almogren et al., 2024) found a positive influence of trust in ChatGPT on perceived usefulness which in turn affected behavioural intention to use ChatGPT in higher education. (Polyportis & Pahos, 2025) also found trust as a significant predictor of attitude towards using ChatGPT which subsequently affected behavioural intention to use ChatGPT.

In most studies, behavioural intention showed strong impact on the use behaviour. It means that if an individual had a strong intention to use a technology, then this strong intention would gradually turn to actual use the technology. (Strzelecki, 2024) showed behavioural intention to use ChatGPT had the most significant effect on use behaviour, followed by habit, and facilitating conditions and the model explained 54.7% of the use behaviour variance. (Romero-Rodríguez et al., 2023) revealed behavioural intention as the only significant predictor of user behaviour to use ChatGPT while facilitating conditions and habit were insignificant predictors. (Faraon et al., 2025) showed behavioural intention and habit as significant predictors of use behaviour of ChatGPT in both Nordic countries and USA while facilitating conditions and personal innovativeness showed insignificant results for both samples. (Cabero-Almenara et al., 2025) also found behavioural intention as the strongest predictor of usage behaviour of ChatGPT, followed by facilitating conditions. [(Budhathoki et al., 2024), (Grassini et al., 2024), (Polyportis & Pahos, 2025)] revealed behavioural intention to use ChatGPT in higher education as a significant predictor of use behaviour but insignificant for facilitating conditions and habit (Grassini et al., 2024). Emon et al. (2023) only showed behavioural intention to use was a significant predictor of actual use of ChatGPT among professionals of Bangladesh. However, studies [(Moradi, 2025), (Rashid, 2025)] revealed behavioural

intention as insignificant predictor of use behaviour of AI suggesting that intention to use was not always translated to actually use AI. In these studies [(Moradi, 2025), (Rashid, 2025)], they showed habit as a significant predictor of AI use behaviour indicating AI actual use was likely to be driven by habit more than by behavioural intention. Another possible reason is that students do not believe the access to organizational and technological infrastructure are available to facilitate the use of AI tools (Yakubu et al., 2025). In the relationship between personal innovativeness and actual use, (Patil et al., 2020) showed personal innovativeness a positive and significant relationship with attitude towards using mobile payment systems which in turn positively influenced behavioural intention and then positively affecting use behaviour.

In respect to mediating effect of behavioural intention, (Ramadhina et al., n.d.) found performance expectancy, effort expectancy, and social influence positively and significantly impact use behaviour through behavioural intention to use Cash on Delivery (COD) payment system. A study by (Kim et al., 2024) revealed that social influence had a significant indirect effect on usage behaviour through behavioural intention, demonstrating social influence significantly contributed to usage behaviour when mediated by behavioural intention, however, no significant indirect effects were observed for performance expectancy, effort expectancy, and facilitating conditions. According to (Selvi & Önem, 2025), the established habits can both directly influence usage behaviour and indirectly create an effect by triggering usage intention and therefore it is crucial to understand how habits shape the actual use behaviour through behavioural intentions. (Selvi & Önem, 2025) also suggested increased intention would trigger actual use by motivating individuals to use technology they find easy and enjoyable. Regarding these hypotheses, (Selvi & Önem, 2025) found electric vehicle usage intention mediated the effect of perceived ease of use and the effect of habits on electric vehicle usage behavior. A study by (Wang & Wang, 2022) showed a direct positive relationship between engagement and mental health, as well as revealing a mediating effect of behavioural intention to use AI on this relationship, highlighted the potential of AI tools in enhancing students' well-being. Based on these findings, the present study investigates the mediating role of behavioural intention to use AI in the effect of each of the ten predictors on AI actual use behaviour.

The present study demonstrates the seven UTAUT2 predictors; performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit together with three new predictors; personal innovativeness, perceived trust, and perceived risk for any significant influence on students' behavioural intention to use AI technologies in higher education. This study proposed to extend a well-established UTAUT2 theory, by adding three new predictors; personal innovativeness, perceived trust, and perceived risk, as factors influencing behavioural intention to use AI technologies. In addition, this present study also investigates for any mediation effect of behavioural intention to use AI on the relationships between each of the ten predictors with AI actual use behaviour. This holistic approach hopes to offer a comprehensive understanding of the multifaceted factors that influence the behavioural intention and AI actual usage behaviour in educational settings.

Research questions

This study focuses to identify the factors influencing the behavioural intention and actual use of AI in higher education. In addition, the study also investigates the mediation effect of behavioural intention in the impact of each factor on AI actual use behaviour. The following research questions are to be addressed in this context:

- i. Which UTAUT2 predictor constructs contribute to behavioural intention to use AI?
- ii. To what extent do the UTAUT2 predictors and behavioural intention to use AI contribute to AI actual use behaviour?
- iii. Does behavioural intention to use AI mediate the effects of UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk on AI actual use behaviour?

METHODOLOGY

Samples and sampling technique

A total of 301 samples were selected non-randomly from six public universities in Malaysia using purposive sampling technique. Samples consist of students pursuing studies in the six universities in various academic programs at diploma and bachelor degree levels.

Instruments and measures

This study aimed to assess the behavioural intention and AI actual usage behaviour among students in public higher education institutions in Malaysia. The survey questionnaires were subsequently emailed to the selected participants, employing purposive sampling due to the unavailability of a comprehensive population list. Seven UTAUT2 predictor constructs adapted from (Venkatesh et al., 2012) and three new predictors were examined in this investigation. The seven UTAUT2 predictors encompassing performance expectancy of 4 items, effort expectancy assessed with 4 items, social influence evaluated through 4 items, facilitating conditions assessed with 4 items, hedonic motivation measured with 3 items, price value evaluated through 3 items, and habits measured with 3 items which were adapted from (Venkatesh et al., 2012). The three new predictors investigated were personal innovativeness assessed with 4 items adapted from (Wang & Wang, 2022), perceived trust with 8 items adapted from ("Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students," 2023), and perceived risk with three items adapted from (W. Li, 2025). This study employs two outcome variables: behavioural intention to use AI, measured with 3 items adapted from (Venkatesh et al., 2012) and AI actual use behaviour, evaluated through 4 items adapted from (Patil et al., 2020). Likert scale with five response choices ranging from strongly disagree to strongly agree was employed to measure the items for each construct.

Data collection

Data were collected using online survey via Google Docs. From the survey disseminated, 301 responses were collected from 20th May 2025 until 18th June 2025. Based on the collected surveys, all 301 were identified as clean and suitable for analysis.

Data analysis

Data are analyzed descriptively and inferentially using SPSS Version 27.0. Research questions 1 and 2 are analyzed using hierarchical multiple regression analysis. Multiple regression analysis using PROCESS v4.2 [64] was employed to address research question 3.

RESULTS

Demographic and AI use personal characteristics of participants

The sample consisted of higher proportion of females (58.5%) than males (41.5%). In terms of age, majority of the respondents were younger with more than half of them (55.1 %) in the 18 – 19 years age group compared to 44.9% of the older students of ages 20 years or more. Bumiputera students emerged as the major ethnicity of respondents with 95%, followed by Chinese/Indians with 4.3%, and other international students with only 0.7% (Table 1). Students participated in the study were from six public universities in Malaysia. Majority (71.1%) of participants pursuing studies in Universiti Teknologi MARA (UiTM), followed by Universiti Teknikal Malaysia Melaka (UTeM) with 20.9%, Universiti Malaysia Perlis (UniMAP) with 5.3%, Universiti Tun Hussein Onn Malaysia (UTHM) with 1.7%, Universiti Teknologi Malaysia (UTM) with 0.7%, and Universiti Malaysia Terengganu (UMT) with 0.3%. For this study, the six universities were categorized into comprehensive universities (UiTM and UTM) and focused universities (UTeM, UTHM, UMT, and UniMAP). For area of study, it is categorized into STEM (Science, Technology, Engineering, Mathematics) programs such as engineering, computer science and non-STEM programs such as accounting, business management, art and design. Majority (56.8%) of respondents pursuing studies in non-STEM programs and 43.2% of them pursuing their studies in STEM programs. A large number of students (66.1%) pursuing studies at diploma level and 33.9% of them pursuing studies at bachelor degree level. Most of students (46.8%) is Year 2 students, 35.5% is Year 1 students, and 17.7% were Year 3 or higher levels students.

Table 1: Demographic and AI use personal characteristics of participants

Demographic/AI use personal characteristics	Category	Frequency	Percentage
Gender	Male	125	41.5
	Female	176	58.5
Age group	Below 20 years old	166	55.1
	20 years or above	135	44.9
Ethnicity	Malay	277	92.0
	Chinese/Indians	13	4.3
	Bumiputera Sabah/Sarawak	9	3.0
	Others	2	0.7
Residential status	Non-resident	33	11.0
	Resident	268	89.0
University	Universiti Teknikal Malaysia Melaka (UTeM)	63	20.9
	Universiti Teknologi Malaysia (UTM)	2	0.7
	Universiti Tun Hussein Onn Malaysia (UTHM)	5	1.7
	Universiti Malaysia Terengganu (UMT)	1	0.3
	Universiti Malaysia Perlis (UniMAP)	16	5.3
	Universiti Teknologi MARA (UiTM Melaka, UiTM Johor, UiTM Perak, UiTM Negeri Sembilan)	214	71.1
Area of study	Management sciences/Social sciences and humanities (Non-STEM)	171	56.8
	Science and technology (STEM)	130	43.2
Level of study	Diploma	199	66.1
	Bachelor degree	102	33.9
Year of study	1	107	35.5
	2	141	46.8
	3	36	12.0
	4 and higher	17	5.7
AI experience	Less than a year	70	23.3
	1 year < 3 years	166	55.1
	3 years or more	65	21.6
AI use frequency	Never/Monthly	34	11.3
	Weekly	147	48.8
	Daily	120	39.9
AI in formal class	No	167	55.5
	Yes	134	44.5
AI use frequency for study	Never/Rarely	16	5.3
	Sometimes	140	46.5
	Always	145	48.2

In term of AI use personal characteristics, more than half of students (55.1%) reported they had 1 year to less than 3 years of AI experience, 23.3% of less than a year experience, and 21.6% of 3 years or more of AI experience. Most of students (48.8%) reported they used AI tools on a weekly basis, 39.9% used on a daily basis, and 11.3% of them either never used or used on a monthly basis. More than half of students (55.5%) reported they did not have formal AI classes and 44.5% of them mentioned they did have formal AI classes in their studies. A large number of students (48.2%) stated they always used AI tools for study, 46.5% sometimes used, and 5.3% never or rarely used AI tools for study. Demographic and AI use personal characteristics of participants are presented in Table 1.

Preliminary analysis

The correlation matrix and descriptive statistics of the variables considered in the study are presented in Table 2. All predictor variables except perceived risk ($r = -0.476$, $p < 0.001$) were significantly and positively correlated with behavioural intention to use AI ranging from $r = 0.591$ to $r = 0.724$. Similarly, all predictor variables and behavioural intention to use AI except perceived risk ($r = -0.512$, $p < 0.001$) were positively and significantly correlated with AI actual use behaviour that ranged from $r = 0.559$ to $r = 0.786$. All predictor variables except perceived risk were positively and significantly intercorrelated that ranged from $r = 0.461$ to $r = 0.796$ while correlation coefficients for perceived risk with other variables ranging from $r = -0.299$ to $r = -0.463$ indicating no violation of multicollinearity of the variables. For the mean scores of the variables, the highest score was performance expectancy (mean = 3.90, SD = 0.689) and the lowest score was perceived risk (mean = 2.26, SD = 0.731). The Cronbach's alpha values of the variables ranged from 0.807 to 0.937 indicating good to excellent consistencies of the scales used.

Table 2: Correlation matrix and descriptive statistics of the variables

		1	2	3	4	5	6	7	8	9	10	11	12
1	Performance expectancy	1											
2	Effort expectancy	0.796***	1										
3	Social influence	0.618***	0.705***	1									
4	Facilitating conditions	0.650***	0.765***	0.741***	1								
5	Hedonic motivation	0.744***	0.736***	0.634***	0.641***	1							
6	Price value	0.461***	0.499***	0.513***	0.540***	0.462***	1						
7	Habit	0.492***	0.562***	0.533***	0.500***	0.487***	0.588***	1					
8	Personal innovativeness	0.569***	0.567***	0.460***	0.552***	0.547***	0.544***	0.583***	1				
9	Perceived trust	0.598***	0.642***	0.561***	0.613***	0.515***	0.647***	0.727***	0.784*	1			
10	Perceived risk	-0.379***	-0.463***	-0.385***	-0.456***	-0.299***	-0.335***	-0.326***	-0.472*	-0.448*	1		
11	Behavioural intention to use AI	0.717***	0.718***	0.591***	0.684***	0.653***	0.614***	0.614***	0.652*	0.724*	-0.476***	1	
12	AI actual use behaviour	0.671***	0.691***	0.559***	0.630***	0.569***	0.546***	0.702***	0.721*	0.783*	-0.512***	0.786***	1
	Mean	3.90	3.77	3.57	3.67	3.87	3.39	3.28	3.61	3.44	2.26	3.63	3.66
	Median	4.00	3.75	3.50	3.75	4.00	3.33	3.00	3.67	3.37	2.33	3.67	3.75
	Standard deviation (SD)	0.689	0.634	0.715	0.643	0.768	0.783	0.904	0.728	0.678	0.731	0.696	0.725
	Minimum	1.50	2.00	1.75	2.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Maximum	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	4.33	5.00	5.00
	Cronbach's alpha	0.877	0.836	0.857	0.873	0.907	0.856	0.914	0.865	0.937	0.807	0.925	0.897
	Number of items	4	4	4	4	3	3	3	3	8	3	6	4

*** $p < 0.001$

Research question 1: Which UTAUT2 predictors contribute to behavioural intention to use AI?

Hierarchical multiple regression analysis is conducted to examine the relationship between seven UTAUT2 predictors and three other constructs with behavioural intention. The factors are divided into two models. Model 1 includes seven UTAUT2 predictors; performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Model 2 includes three other variables: personal innovativeness, perceived trust, and perceived risk. Behavioural intention is the outcome variable. In model 1, all the seven predictors significantly explained 68.1% of the variance in behavioural intention ($F(7, 293) =$

89.876, $p < 0.001$). The results revealed positive significant relationships between performance expectancy ($t = 4.950$, $p < 0.001$), facilitating conditions ($t = 3.664$, $p < 0.001$), price value ($t = 4.636$, $p < 0.001$), and habit ($t = 4.111$, $p < 0.001$) with behavioural intention. Performance expectancy (Beta = 0.293, $p < 0.001$) emerged as the strongest predictor of behavioural intention, followed by facilitating conditions (Beta = 0.214, $p < 0.001$), price value (Beta = 0.203, $p < 0.001$), and habit (Beta = 0.184, $p < 0.001$). The results indicated that the original UTAUT2 structure revealed performance expectancy, facilitating conditions, price value, and habit significantly and positively affected behavioural intention, while effort expectancy, social influence, and hedonic motivation did not show significant impacts on behavioural intention to use AI.

After controlling for UTAUT2 predictors and introducing personal innovativeness, perceived trust, and perceived risk in model 2, the results showed a significant relationship to predict behavioural intention with 71% variability ($F = 71.052$, $p < 0.001$). The explanatory variance increased by 2.9%, with performance expectancy, facilitating conditions, hedonic motivation, price value, perceived trust, and perceived risk reaching significant levels. The predictive power of performance expectancy was the highest (Beta = 0.245, $t = 4.247$, $p < 0.001$), followed by perceived trust (Beta = 0.210, $t = 3.188$, $p < 0.01$), facilitating conditions (Beta = 0.155, $t = 2.715$, $p < 0.01$), price value (Beta = 0.139, $t = 3.167$, $p < 0.01$), hedonic motivation (Beta = 0.119, $t = 2.194$, $p < 0.05$), and perceived risk (Beta = -0.097, $t = -2.557$, $p < 0.05$). Effort expectancy, social influence, habit, and personal innovativeness did not show significant impacts on behavioural intention. Table 3 highlights the results.

Table 3: Hierarchical Multiple regression analysis results predicting behavioural intention to use AI

Predictors	Model 1				Model 2			
	B	Std error	Beta	t	B	Std error	Beta	t
Performance expectancy	0.296	0.060	0.293	4.950***	0.248	0.058	0.245	4.247***
Effort expectancy	0.124	0.075	0.113	1.652	0.062	0.074	0.057	0.844
Social influence	-0.082	0.052	-0.084	-1.557	-0.073	0.051	-0.075	-1.438
Facilitating conditions	0.231	0.063	0.214	3.664***	0.168	0.062	0.155	2.715**
Hedonic motivation	0.076	0.049	0.084	1.548	0.108	0.049	0.119	2.194*
Price value	0.181	0.039	0.203	4.636***	0.124	0.039	0.139	3.167**
Habit	0.141	0.034	0.184	4.111***	0.064	0.037	0.083	1.707
Personal innovativeness					0.028	0.053	0.030	0.541
Perceived trust					0.216	0.068	0.210	3.188**
Perceived risk					-0.093	0.036	-0.097	-2.557*
R	0.825				0.843			
R square	0.681				0.710			
R square change	0.681				0.029			
F	89.876***				71.052***			

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Dependent variable – Behavioural intention

The findings indicate high levels of performance expectancy, facilitating conditions, hedonic motivation, price value, perceived trust, and low perceived risk together determined stronger behavioural intention to use AI. Results also indicated only performance expectancy, facilitating conditions, hedonic motivation, and price value of the original UTAUT2 while perceived trust and perceived risk of the new extended structure determined the behavioural intention. Students were more likely intended to use AI if they believed it would help them to get better grades, understand concepts faster, or write better assignments. Students also tended to adopt AI if they had good facilitating conditions like easy access to internet, had access to devices, good training for lecturers, and good university support. Students tended to have greater intention to use AI if they felt fun and enjoyed about AI. The price value is also positive as students perceived the value-for-money of AI technologies in terms of benefits such as efficiency, convenience, and accuracy that outweighed the cost and this perception influences their willingness or intention to use these technologies. Students would have high intention to use AI if they had high perceived trust on AI such as no misleading information, did not violate academic integrity, and did not invade their privacies. The level of perceived risk would also be lower if students' behaviour intentions to use AI were at high levels.

Research question 2: To what extent do the UTAUT2 predictors, personal innovativeness, perceived trust, perceived risk, and behavioural intention to use AI contribute to AI actual use behaviour?

Hierarchical multiple regression analysis was also performed to address research question 2. All constructs in the study were divided into three models. Model 1 includes seven UTAUT2 predictors; performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Model 2 includes three added independent variables: personal innovativeness, perceived trust, and perceived risk. Model 3 includes behavioural intention. As shown in Table 4, the UTAUT2 predictor constructs in model 1 significantly explained 66.3% of the variance in AI actual use behavior ($F = 82.401$, $p < 0.001$) with habit ($Beta = 0.417$, $t = 9.075$, $p < 0.001$), performance expectancy ($Beta = 0.284$, $t = 4.664$, $p < 0.001$), facilitating conditions ($Beta = 0.173$, $t = 2.877$, $p < 0.01$), and effort expectancy ($Beta = 0.164$, $t = 2.334$, $p < 0.05$) reaching significance levels. Students with higher levels of performance expectancy, effort expectancy, facilitating conditions, and habit were more likely to use AI. Social influence, hedonic motivation, and price value did not significantly predict the actual use behavior of AI. After controlling for UTAUT2 predictors and introducing personal innovativeness, perceived trust, and perceived risk in model 2, the results showed a significant relationship to predict the actual use behaviour with 74.1% variability ($F = 83.157$, $p < 0.001$). The explanatory variance increased by 7.8%, with performance expectancy, effort expectancy, habit, personal innovativeness, perceived trust, and perceived risk reaching significant levels. The predictive power of habit was the highest ($Beta = 0.257$, $t = 5.585$, $p < 0.001$), followed by perceived trust ($Beta = 0.257$, $t = 4.127$, $p < 0.001$), personal innovativeness ($Beta = 0.166$, $t = 3.200$, $p < 0.01$), performance expectancy ($Beta = 0.200$, $t = 3.660$, $p < 0.001$), and perceived risk ($Beta = -0.125$, $t = -3.476$, $p < 0.001$) indicating high levels of habit, perceived trust, personal innovativeness, performance expectancy, and with low perceived risk together significantly associated with higher AI actual use behavior. After incorporating behavioural intention in model 3, including all other predictors, the total explanatory variance rose to 76.9% ($F = 87.294$, $p < 0.001$), specifying that the additive behavioural intention increased the explanatory variance by 2.7%. The most significant predictor of AI actual use behaviour was behavioural intention ($Beta = 0.306$, $t = 5.832$, $p < 0.001$), followed by habit ($Beta = 0.231$, $t = 5.283$, $p < 0.001$), perceived trust ($Beta = 0.192$, $t = 3.208$, $p < 0.001$), personal innovativeness ($Beta = 0.157$, $t = 3.190$, $p < 0.01$), performance expectancy ($Beta = 0.124$, $t = 2.337$, $p < 0.05$), perceived risk ($Beta = -0.095$, $t = -2.762$, $p < 0.01$), and price value ($Beta = -0.085$, $t = -2.130$, $p < 0.05$) indicating high levels of behavioural intention to use AI, habit, perceived trust, personal innovativeness, performance expectancy, and with low perceived risk, and low price value together significantly associated with stronger AI actual use behavior. Effort expectancy, social influence, facilitating conditions, and hedonic motivation did not significantly have effects on AI actual use behaviour. Table 4 reveals the results.

Table 4: Hierarchical Multiple regression analysis results predicting AI actual use behaviour

Predictors	Model 1				Model 2				Model 3			
	B	Std error	Beta	t	B	Std error	Beta	t	B	Std error	Beta	t
Performance expectancy	0.299	0.064	0.284	4.664***	0.210	0.057	0.200	3.660***	0.131	0.056	0.124	2.337*
Effort expectancy	0.188	0.081	0.164	2.334*	0.104	0.072	0.091	1.440	0.084	0.069	0.074	1.229
Social influence	-0.079	0.056	-0.078	-1.405	-0.048	0.050	-0.048	-0.971	-0.025	0.047	-0.025	-0.531
Facilitating conditions	0.195	0.068	0.173	2.877**	0.084	0.061	0.074	1.378	0.030	0.058	0.027	0.518
Hedonic motivation	-0.053	0.053	-0.056	-1.000	-0.028	0.048	-0.030	-0.586	-0.063	0.046	-0.066	-1.358
Price value	0.056	0.042	0.060	1.340	-0.040	0.039	-0.043	-1.026	-0.079	0.037	-0.085	-2.130*
Habit	0.334	0.037	0.417	9.075***	0.206	0.037	0.257	5.585***	0.185	0.035	0.231	5.283***
Personal innovativeness					0.165	0.052	0.166	3.200**	0.156	0.049	0.157	3.190**
Perceived trust					0.275	0.067	0.257	4.127***	0.206	0.064	0.192	3.208***
Perceived risk					-0.124	0.036	-0.125	-3.476***	-0.095	0.034	-0.095	-2.762**
Behavioral intention									0.319	0.055	0.306	5.832***

R	0.814	0.861	0.877
R square	0.663	0.741	0.769
R square change	0.663	0.078	0.027
F	82.401***	83.157***	87.294***

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Dependent variable – Actual use behavior

Research question 3: Does behavioural intention to use AI mediate the effects of UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk on AI actual use behaviour?

The mediation analysis using multiple regression PROCESS v4.2 [64] (Model 4) was conducted to assess whether behavioural intention to use AI mediate the relationships between UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk with AI actual use behaviour. Results revealed that behavioural intention to use AI had partial mediation effects on the relationships between all UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk with AI actual use behaviour. Results showed performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, and perceived trust positively and significantly influenced AI actual use behaviour, both directly and indirectly via behavioural intention to use AI. However, perceived risk negatively and significantly affecting AI actual use behaviour, both directly and indirectly through behavioural intention to use AI. Results are presented in Table 5.

The positive and significant direct and indirect effects of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, and perceived trust via behavioural intention to actual use AI implying students with higher performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, and perceived trust would have greater intention to use AI technologies and this intention would be translated to the stronger action of using the technologies. This means that students' belief on AI enhances their academic performance, ease of use, social influence, facilitating supports, fun and enjoyment, price worth, prior habit, innovativeness, and trust foster a strong intention to use AI, which ultimately influences their decision to actually use AI technology. The negative signs for direct and indirect effects of perceived risk via behavioural intention to use AI implying students with lower perceived risk would have greater intention to use AI technologies and this intention would be translated to the stronger action of using the technologies. These results underscore the important roles of UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk in enhancing behavioural intention to use AI and hence improving AI actual use behaviour among university students.

Table 5: Mediating effects of behavioural intention to use AI on the relationships between UTAUT2 predictors, personal innovativeness, perceived trust, and perceived risk with AI actual use behaviour using PROCESS v4.2 [64]

Relationships	X → M (a)	M → Y (b)	Direct effect X → M → Y (c')	Total effect X → Y (c)	Indirect effect (a*b) = (c – c')	Mediation type
PE (X) → BI (M) → AUB (Y)	0.7250***	0.6540***	0.2321***	0.7063***	0.4741***	Partial
EE (X) → BI (M) → AUB (Y)	0.7906***	0.6227***	0.3000***	0.7906***	0.4906***	Partial
SI (X) → BI (M) → AUB (Y)	0.5755***	0.7289***	0.1479***	0.5674***	0.4195***	Partial
FC (X) → BI (M) → AUB (Y)	0.7407***	0.6944***	0.1967***	0.7110***	0.5143***	Partial
HM (X) → BI (M) → AUB (Y)	0.5919***	0.7527***	0.0917*	0.5372***	0.4455***	Partial
PV (X) → BI (M) → AUB (Y)	0.5462***	0.7539***	0.0939*	0.5057***	0.4118***	Partial
HA (X) → BI (M) → AUB (Y)	0.4729***	0.5930***	0.2828***	0.5633***	0.2804***	Partial
PI (X) → BI (M) → AUB (Y)	0.6234***	0.5725***	0.3611***	0.7181***	0.3569***	Partial
PT (X) → BI (M) → AUB (Y)	0.7438***	0.4790***	0.4814***	0.8377***	0.3563***	Partial
PR (X) → BI (M) → AUB (Y)	-0.4531***	0.7301***	-0.1776***	-0.5084***	-0.3308***	Partial

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

PE – Performance expectancy EE – Effort expectancy SI – Social influence FC – Facilitating conditions
 HM – Hedonic motivation

PV – Price value HA – Habit PI – Personal innovativeness PT – Perceived trust PR – Perceived risk
 AUB – AI actual use behaviour

DISCUSSION AND IMPLICATIONS

Variables related to behavioural intention to use AI

The research findings provide valuable insights into the factors influencing the behavioural intention to use AI and AI actual use behaviour among Malaysian university students. The findings indicated that performance expectancy, facilitating conditions, hedonic motivation, price value, perceived trust, and perceived risk significantly influenced students' behavioural intention to use AI. Among these predictors, performance expectancy demonstrated the strongest positive influence on behavioral intentions, followed by perceived trust, facilitating conditions, price value, and hedonic motivation, while perceived risk demonstrated a negative influence on behavioural intention to use AI. Performance expectancy had the strongest positive effect on intention to use AI, echoing findings by [(Senali et al., 2023), (Menon & Shilpa, 2023), (Romero-Rodríguez et al., 2023), (Strzelecki, 2024), (Budhathoki et al., 2024), (Grassini et al., 2024), (Poudel & Bastakoti, 2024), (Biloš & Budimir, 2024)] on intention to use ChatGPT. This implies students with high belief that AI can enhance their academic tasks are more likely to express intentions to use it. The findings were also in accordance with (Chao, 2019) who found behavioural intention was significantly and positively influenced by trust and performance expectancy. Results also showed perceived trust significantly and positively influenced behavioural intention to use AI which was supported by previous research [(Kandoth & Shekhar, 2022), (Su et al., 2025)]. According to (Seo & Lee, 2021), trust can enhance users' confidence in technology and thus uphold their intentions to use the technology.

Facilitating conditions positively influenced behavioural intention to use AI, aligning with previous studies [(Chatterjee & Bhattacharjee, 2020), (Menon & Shilpa, 2023), (Emon et al., 2023), (Poudel & Bastakoti, 2024), (Polyportis & Pahos, 2025)] but contrasts with [(Strzelecki, 2024), (Romero-Rodríguez et al., 2023), (Su et al., 2025)] who found no significant relationship between facilitating conditions and intentions to use ChatGPT. Results also found hedonic motivation and price value positively affected the intentions to use AI, in line with previous research [(Strzelecki, 2024), (Romero-Rodríguez et al., 2023)] implying that students who felt fun and enjoyed with technologies as well as those who believed AI would give good value on adopting it tended to have higher intentions to use it. The current study also found significant negative influence of perceived risk on behavioural intention to use AI in corroboration with [(Senali et al., 2023), (W. Li, 2025), (Su et al., 2025)]. Perceived risk negatively affected students' attitudes and emotions (Chatterjee & Bhattacharjee, 2020), making them more resistant to adopting the technology (W. Li, 2025).

All these findings indicated that students' intentions to use AI technologies would increase when they believed AI would help them to perform tasks better or more efficient as well as having sufficient supportive infrastructure like easy access to resources, adequate training, and technical support in supporting them to use AI. Students' intentions would also increase if they felt enjoyed and fun on adopting the AI, believed AI would give good value, and having high trust to adopt AI. On the other hand, students' intentions to use AI would decline if they perceived AI was risky and unsafe to use. Conversely, results revealed the influences of effort expectancy, social influence, habit, and personal innovativeness on behavioural intentions to use AI did not reach statistical significances. These findings agreed with previous research [(Romero-Rodríguez et al., 2023), (Grassini et al., 2024)] who showed effort expectancy and social influence insignificantly affecting intention to use ChatGPT and (Chao, 2019) who revealed insignificant relationship between effort expectancy with intention to use mobile learning. Result of the present study is in contrast with (Strzelecki, 2024) who found effort expectancy, social influence, habit, and personal innovativeness positively significantly influenced intention to use ChatGPT. The result was also inconsistent with (Budhathoki et al., 2024) who showed significant effects of effort expectancy and social influence on intention to use ChatGPT among students using language model in Nepal and United Kingdom. Finding of the current study revealed insignificant association between personal innovativeness and

AI actual use behaviour was in line with [(Flavián et al., 2022), (Krishnanraw & Ismail, 2025)] who found innovativeness did not significantly enhance the intention to use AI technologies.

The possible explanation for inconsistent findings in effort expectancy may be due to the present study consisted of more tech-savvy users that they would find easier to use AI which reduced the impact of effort expectancy. Furthermore, from the present study, almost 62% students were familiar and very familiar with AI technologies that would make them easier to use the AI. As for inconsistent finding in social influence, the participants in this current study were more than fifty percent comprised of younger users (less than 20 years old) that considered more about fun or enjoyment of using AI rather than social pressure. Personal innovativeness has less or no influence on behavioural intention to use AI may be due to AI tool such as ChatGPT is increasingly integrated into education, making the technology widely accessible and normalized. Moreover, the finding from the current study reveals almost 90% students are using chatbots in their daily lives as well as for learning purposes.

Variables associated with AI actual use behaviour

Results of the current study revealed that the most significant predictor of AI actual use behaviour was behavioural intention, followed by habit, perceived trust, personal innovativeness, performance expectancy, perceived risk, and price value. From the findings, among the UTAUT2 predictors, only behavioural intention to use, performance expectancy, habit, and price value together with the newly added predictors (personal innovativeness, perceived trust, and perceived risk) showed significant influence on AI actual use behaviour. The findings indicated that greater behavioural intention to use AI, habit, perceived trust, personal innovativeness, performance expectancy, and with decreased perceived risk and lower price value together significantly associated with stronger AI actual use behavior.

Behavioural intention to use AI positively and significantly influenced AI actual use behaviour among students at higher education level. Many previous research [(Chatterjee & Bhattacharjee, 2020), (X. Li et al., 2022), (Emon et al., 2023), (Romero-Rodríguez et al., 2023), (Strzelecki, 2024), (Budhathoki et al., 2024), (Grassini et al., 2024), (Acosta-Enriquez et al., 2024), (Ramadhina et al., n.d.), (Q. Wu et al., 2025), (Faraon et al., 2025)] supported this finding, however, in contrast with studies [(Moradi, 2025), (Rashid, 2025)]. Findings by [(Moradi, 2025), (Rashid, 2025)] suggested that not all times behavioural intention is translated to actually use the AI. Another earlier studies [(Raza et al., 2021), (Abbad, 2021)] also found positive link between behavioural intention and actual use of Learning Management System during COVID-19 pandemic. Habit and behavioural intention to use AI were significantly associated with actual use behaviour supported previous research [(Romero-Rodríguez et al., 2023), (Strzelecki, 2024), (Grassini et al., 2024)] and performance expectancy significantly influenced by actual use behaviour was consistent with (Jain et al., 2022). The present result also corroborated with (Q. Wu et al., 2025) who showed habit and personal innovativeness positively and significantly influenced actual use behaviour of ChatGPT. Moreover, (Q. Wu et al., 2025) emphasized on the innovative role in enhancing generative AI usage as revealed from the positive moderating effect of personal innovativeness on the relationship between behavioural intention and usage behaviour while habit negatively moderates this relationship. This finding indicates that students with strong intentions to use AI are not likely to be constrained by the lacking of habit to actual use AI. Thus, the lack of habit to actual use AI does not limit the AI actual use of the users with strong intentions to use AI. The finding also implies behavioural intentions to use AI is strongly associated with actual use of AI when the users have strong personal innovativeness backgrounds.

Studies by [(Romero-Rodríguez et al., 2023), (Strzelecki, 2024)] found positive relationship between price value and behavioural intention to use ChatGPT which in turn had positive effect on actual use behaviour, however no relationship was shown between price value and actual use behaviour. Interestingly, this current study showed price value positively affected behavioural intention to use AI but negatively associated with AI actual use behaviour. The possible explanation for this finding is that before using the AI, students may perceive high price value that offers good value and worth the cost, which increases their intentions to use it. However, after the actual use of AI, they may experience some hidden costs either monetary or non-monetary such as limited free features, that discouraged the AI actual usage. Another possible reason is students may overestimate the benefits

of AI which increases their intentions to use AI before using it, however after actual using it, they realized AI did not match their expectations, which in turn discouraged them to the actual usage. These results indicated that students who intended to use AI, had prior habits or routine with AI tools, those who trusted the AI tools, those who like trying new technologies, and those who believe AI helps to improve their academic performance would more likely to actual use them. However, students who believed that AI might lead to negative consequences and those who felt adopting AI tools were not worth the price would less likely to use them.

Out of ten predictors considered, only performance expectancy, price value, perceived trust, and perceived risk significantly influenced both behavioural intentions to use AI and AI actual use behaviour. From these predictors, only performance expectancy and price value were UTAUT2 predictors while perceived trust and perceived risk were the newly added predictors into the original UTAUT2 model. Performance expectancy and perceived trust positively influenced while perceived risk negatively influenced behavioural intention to use AI and AI actual use behaviour. Students believed that AI tools were helping them to achieve and fulfil their academic tasks that increase their intentions to use AI which encouraged them to actually use AI. If students had trust on using technologies, then their confidence to use the technologies would be enhanced which in turn increased their intentions to use and finally engaged with the technologies (Seo & Lee, 2021). Students believed that perceived risk would decrease their intention to use AI which in turn discouraged them to actually use AI. Findings also showed facilitating conditions and hedonic motivation positively influenced behavioural intentions to use AI but did not significantly influence AI actual use while habit and personal innovativeness positively affected AI actual use but did not affect behavioural intention to use AI. Students may have intentions to use AI because they believe that facilitating conditions such as resources, technical support, or infrastructure supported them to use AI, but this may not be translated into actual usage if they have other barriers such as time or habit to do so. Students may have intentions to use AI because they find it enjoying or interesting, and continue to use it, if they have opportunities and motivation to do so as there are significant effects of opportunity and motivation on internet engagement as confirmed by (Prensky, 2001) suggesting that students will continue to use AI if only they have opportunities and motivation to do so. Students with prior or routine habit of actually using AI may not have intentions to use AI, but will automatically use it. Students with innovative minds and willingness to try new technologies may just using it without forming the intention to use it.

Findings also revealed insignificant influences of effort expectancy and social influence on AI actual use behaviour. The possible explanation for insignificance of effort expectancy is that more than half of the students are familiar and very familiar with AI technologies which make them easy to use the technologies. With regard to social influence, the possible explanation is that majority of students are young students of below 20 years old that can be categorized as tech-savvy users and digital native (Polyportis, 2023), they use the technology not because of social influences but more likely to make friend with the technology. Moreover, according to (Venkatesh & Davis, 2000), the role of social influence seemed to be eroded over time due to individuals gained direct experience with a system over time, such that they relied less on social information in forming perceived usefulness and intention, but continued to judge a system's usefulness on the basis of potential status benefits resulting from use.

Mediation effects of behavioural intention to use AI

Results of the current study showed that behavioural intention to use AI played a mediating role in the relationship between each UTAUT2 predictor and each of the three added predictors with AI actual use behaviour. The findings showed that behavioural intention as significant mediator for each of the relationship, which suggested behavioural intention to use AI is a central pathway but it is not an exclusive pathway through which performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, perceived trust, and perceived risk influence actual AI use. Taken together, these findings suggest that students with high levels of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, perceived trust, and lower level of perceived risk will have strong intentions to use AI. However, even without strong intentions, students with high levels of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, personal innovativeness, perceived trust, and low

perceived risk, they may still use AI directly which probably because of their familiarities and knowledge about AI.

Theoretical and practical implications

This research makes contributions at theoretical and practical levels to understanding AI behavioural intention and AI actual use behaviour within student settings. It enriches the understanding of behavioural intention and actual use behaviour of AI in student contexts, by integrating personal innovativeness, perceived trust, and perceived risk into the UTAUT2 model. This expansion acknowledges the personal traits dimension in addition to the cognitive and affective aspects of technology adoption. The extended UTAUT2 worked well in explaining 71% of the variance in behavioural intention as well as explained 76.9% of the variance in AI actual use behaviour. Therefore, this study contributes theoretically by proposing an extended model that shows the impacts on behavioural intention to use AI and on AI actual use behaviour in student context. This fills a knowledge gap, and extending UTAUT2 model in student context by including personal innovativeness, perceived trust, and perceived risk constructs into the model. To our best of knowledge, this study is one of the first that investigated the mediating influences of behavioural intention to use AI on the associations between UTAUT2 predictors and three newly added predictors. Behavioural intention has been studied as a mediator of the performance expectancy, effort expectancy, and social influence-usage behaviour relationship in technology acceptance models for Cash on Delivery (COD) System Users in Marketplaces (Ramadhina et al., n.d.), its mediating role in the AI actual use behaviour in educational context has not been explored.

With regard to practical implications, (Polyportis, 2023) emphasized the significant role of behavioural intention to use ChatGPT in predicting changes in usage behaviour that underscores the need for supportive institutional environments. To ensure students' behavioural intention to use AI translated to actual use of AI, supportive institutional environment is important which involves addressing factors like policies, privacy concerns, and ethical considerations (Kooli, 2023). By identifying links between personal innovativeness, perceived trust, and perceived risk and UTAUT2 constructs, the study offers practical insights for educators, developers, and policy makers seeking to enhance AI adoption in higher education student setting. To increase AI adoption, higher educational institutions should promote habit formation by encouraging routine use of AI tools in building the trust to use AI technologies, give support to innovative students through flexible and exploration opportunities to reduce the thought of risk, and bridge the gap between intention and usage by embedding AI use into academic tasks, making the step clearer from intention to use to actually use AI.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

Conclusion

This study aimed to examine university students' adoption and actual use of AI technologies in Malaysia, employing the UTAUT2 predictors together with three newly added predictors. The study extends the UTAUT2 model by integrating personal innovativeness, perceived trust, and perceived risk, highlighting the personal traits, cognitive, and affective aspects of technology adoption. Results indicated that performance expectancy, price value, perceived trust, and perceived risk significantly impacted both intents to use and actual use of AI. Facilitating conditions and hedonic motivation only predicted behavioural intention while habit and personal innovativeness only influenced AI actual use. Performance expectancy is the strongest predictor for behavioural intention and the most influential predictor of AI actual use is behavioural intention to use.

The study underscores the importance of strengthening students' behavioural intention to use AI, enhancing the performance-based aspects, promoting habit through routine use of AI tools, building trust in AI technologies, emphasizing the good values of AI, and supporting innovative students through flexible and exploration opportunities, in order to promote AI adoption and actual utilization. The study also emphasizes on reducing the perceived risk that can deter students from their intention to use and actual adoption of AI tools. In addition, the mediation effect of behavioural intention to use AI is also highlighted. Integration of AI into higher education empowers educators to harness its potential, thus giving rise to innovative and enriching educational experiences that equip students for the demands of the modern world (Osman et al., 2023). Overall, this research provides

valuable insights for both theory and practice as well as enhances the understanding of AI tool adoption and actual use in higher education.

Limitations and future research

This research is subject to some limitations. The research has identified these limitations and directions for future research. First, this research employed a non-probability purposive sampling method to collect the data from students studying at public universities via lecturers based on acquaintances of the researchers, who are currently teaching the students in the universities. The approach is very common and has been widely utilized in the past studies on the acceptance of a variety of technology. It would be useful for future studies to employ probability sampling for more representative results. Second, all respondents for this study are studying in public universities. In the future, respondents must also come from private universities where comparisons can be made in terms of the acceptance of AI technologies using the extended model proposed in this study. Third, this study only includes focused and comprehensive universities but research university is not included, making the study not representative of the public universities population in Malaysia in the behavioural intention and use behaviour of AI technologies among university students in Malaysia that leaves significant gaps in the understanding of the broader educational context. Lastly, only students at lower and middle study levels are included in the study, excluding the postgraduate students. Future studies should also include postgraduate students as they are part of the students population, so that comparison can be made between study levels in terms of behavioural intention and actual use of AI.

REFERENCES

1. Vieriu, A. M., & Petrea, G. (2025). The Impact of Artificial Intelligence (AI) on Students' Academic Development. *Education Sciences*, 15(3), 343. <https://doi.org/10.3390/educsci15030343>
2. 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/10.1007/s10639-020-10159-7>
3. J.A. Oravec, Artificial intelligence implications for academic cheating: expanding the dimensions of responsible human-AI collaboration with ChatGPT, *J. Interact. Learn. Res.* 34 (2023) 213–237.
4. Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-Assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. *Frontiers in Psychology*, 13, 870777. <https://doi.org/10.3389/fpsyg.2022.870777>
5. 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
6. Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178.
7. Abbad, M. M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies*, 26(6), 7205–7224. <https://doi.org/10.1007/s10639-021-10573-5>
8. Zacharis, G., and K. Nikolopoulou. 2022. Factors predicting university students' behavioral intention to use e-learning platforms in the post-pandemic normal: An UTAUT2 approach with 'learning value'. *Education and Information Technologies* 27 (9):12065–82. doi:10.1007/s10639-022-11116-2.
9. Chao C-M (2019) Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. *Front. Psychol.* 10:1652. doi: 10.3389/fpsyg.2019.01652
10. Ridho Bramulya Ikhsan, Hartiwi Prabowo, and Yuniarty (2021). Drivers of the Mobile-Learning Management System's Actual Usage: Applying the UTAUT Model. *ICIC Express Letters, Part B: Applications*, Vol.12, No.11, 2021
11. Nahil Abdallah, Odeh Abdallah, OM Bohra (2021). Factors Affecting Mobile Learning Acceptance in Higher Education: An Empirical Study. (IJACSA) *International Journal of Advanced Computer Science and Applications*, Vol. 12, No. 4, 2021

12. Nguyen, T. M., & Teng, H. C. (2022). A Study of Mobile Devices' Acceptance in Developing EFL Listening Skill among Vietnamese High School Learners. *International Journal of TESOL & Education*, 2(2), 95- 118. DOI: <https://doi.org/10.54855/ijte.22226>
13. Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, 59(2), 183-208. <https://doi.org/10.1177/0735633120960421>
14. De Blanes Sebastián, M. G., Guede, J. R. S., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, 13, 993935. <https://doi.org/10.3389/fpsyg.2022.993935>
15. Kingsley Ofosu-Ampong, Bryan Acheampong, Mark-Oliver Kevor, Fred Amankwah-Sarfo (2023). Acceptance of Artificial Intelligence (ChatGPT) in Education: Trust, Innovativeness and Psychological Need of Students. *Information and Knowledge Management* www.iiste.org Vol.13, No.4, 2023 ISSN 2224-5758 (Paper) ISSN 2224-896X (Online).
16. Emon, M. M. H., Hassan, F., Nahid, M. H., & Rattanawiboonsom, V. (2023). Predicting Adoption Intention of Artificial Intelligence CHATGPT. *AIUB Journal of Science and Engineering (AJSE)*, 22(2), 189–199. <https://doi.org/10.53799/ajse.v22i2.797>
17. Su, J., Wang, Y., Liu, H., Zhang, Z., Wang, Z., & Li, Z. (2025). Investigating the factors influencing users' adoption of artificial intelligence health assistants based on an extended UTAUT model. *Scientific Reports*, 15(1), 18215. <https://doi.org/10.1038/s41598-025-01897-0>
18. Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamaní Jordan, O., López Roca, C., & Saavedra Tirado, K. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychology*, 12(1), 255. <https://doi.org/10.1186/s40359-024-01764-z>
19. Artur Strzelecki (2024). Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education* (2024) 49:223–245 <https://doi.org/10.1007/s10755-023-09686-1>
20. Patrick M. Cortez, Ardivin Kester S. Ong, John Francis T. Diaz, Josephine D. German, Singh Jassel Satwant Singh Jagdeep (2024). Analyzing Preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon* 10 (2024) e25896
21. Simone Grassini, Maren Linnea Aasen & Anja Møgelvang (2024) Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model, *Applied Artificial Intelligence*, 38:1, 2371168, DOI: 10.1080/08839514.2024.2371168
22. Pushp Patil, Kuttamani Tamilmani, Nripendra P. Rana, Vishnupriya Raghavan (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 (2020) 102144
23. Farhana Hanim Mohsin, Norhayati Md Isa, Khairunnisa Ishak, and Hatijah Mohamed Salleh (2024). Navigating the Adoption of Artificial Intelligence in Higher Education. *International Journal of Business and Technopreneurship*, Volume 14, No 1, February 2024 [109-120]
24. Athanasios Polyportis & Nikolaos Pahos (2025) Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy, *Behaviour & Information Technology*, 44:2, 315-336, DOI: 10.1080/0144929X.2024.2317364
25. Cao, G., Duan, Y., Edwards, J., and Dwivedi, Y. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation* 106:102312. doi: 10.1016/j.technovation.2021.102312
26. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
27. Jyashree Krishnanraw and Kamisah Ismail (2025). Behavioural Intention to use Artificial Intelligence (AI) among Accounting Students: Evaluating the Effect of Technology Readiness. *Management and Accounting Review*, Volume 24 No 1, April 2025
28. Räisänen, M, Postareff, L, Mattsson, M & Lindblom-Ylänne, S 2020, ' Study-related exhaustion: First-year students' use of self-regulation of learning and peer learning and perceived value of peer support',

- Active Learning in Higher Education, vol. 21, no. 3, pp. 173-188.
<https://doi.org/10.1177/1469787418798517>
29. Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A. E., & Baneres, D. (2022). Applying the UTAUT Model to Explain the Students' Acceptance of an Early Warning System in Higher Education. *Computers & Education*, 182, 104468. <https://doi.org/10.1016/j.compedu.2022.104468>
 30. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
 31. Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, 61, 404–414
 32. Jain R, Garg N and Khera SN (2022) Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. *Front. Psychol.* 13:893691. doi: 10.3389/fpsyg.2022.893691
 33. Limayem, M., Hirt, S. G., and Cheung, C. M. K. 2007. “How Habit Limits the Predictive Power of Intentions: The Case of IS Continuance”, *MIS Quarterly* (31:4), pp. 705-737
 34. Cabrera-Sánchez, J.-P., Villarejo-Ramos, Á. F., Liébana-Cabanillas, F., & Shaikh, A. A. (2021). Identifying relevant segments of AI applications adopters: Expanding the UTAUT2's variables. *Telematics and Informatics*, 58, Article 101529. <https://doi.org/10.1016/j.tele.2020.101529>
 35. Su-Chen (Cecilia) Lin, Mei-Chen Chuang, Chen-Yuan Huang, and Chia-En Liu (2023). Nursing Staff's Behavior Intention to Use Mobile Technology: An Exploratory Study Employing the UTAUT 2 Model. *SAGE Open* October-December 2023: 1–14 The Author(s) 2023 DOI: 10.1177/21582440231208483 journals.sagepub.com/home/sgo
 36. Audrey Saudjhana & Herman (2023). Behavioral Intention and Adoption of Digital Bank Mobile Application Among Housewives Using Mixed Method Approach. *Journal of Computer Networks, Architecture and High-Performance Computing* Volume 5, Number 1, January 2023
 37. Rogers, E. M. (2003), *Diffusion of innovations* (5th ed.). New York, US: Free Press
 38. Muhammad Shoaib Farooq, Maimoona Salam, Norizan Jaafar, Alain Fayolle, Kartinah Ayupp, Mirjana Radovic-Markovic, Ali Sajid (2017). "Acceptance and use of lecture capture system (LCS) in executive business studies: extending UTAUT2", *Interactive Technology and Smart Education*, <https://doi.org/10.1108/ITSE-06-2016-0015>
 39. E. Toreini, M. Aitken, K. Coopamootoo, K. Elliott, C. G. Zelaya, and A. Van Moorsel, “The relationship between trust in AI and trustworthy machine learning technologies,” in *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 2020, pp. 272–283
 40. Featherman, M. S., and Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies* 59, 451–474. doi: 10.1016/s1071-5819(03)00111-3
 41. Susanto, T. D., & Goodwin, R. (2011). In M. Janssen, H. J. Scholl, M. A. Wimmer, & Y. H. Tan (Eds.), *User acceptance of SMS-based e-government services* (Vol. 6846, pp. 75–87). *EGOV 2011, INCS*.
 42. Tao, W., Gao, S., & Yuan, Y. (2023). Boundary crossing: An experimental study of individual perceptions toward AIGC. *Frontiers in Psychology*, 14, 1185880. <https://doi.org/10.3389/fpsyg.2023.1185880>
 43. Wu, J., Gan, W., Chen, Z., Wan, S., & Lin, H. (2023). AI-Generated Content (AIGC): A survey. *arXiv preprint arXiv:2304.06632*
 44. Weiyi Li (2025) A Study on Factors Influencing Designers' Behavioral Intention in Using AI-Generated Content for Assisted Design: Perceived Anxiety, Perceived Risk, and UTAUT, *International Journal of Human-Computer Interaction*, 41:2, 1064-1077, DOI: 10.1080/10447318.2024.2310354 <https://doi.org/10.1080/10447318.2024.2310354>
 45. Lang, C. (2018). Perceived risks and enjoyment of access-based consumption: Identifying barriers and motivations to fashion renting. *Fashion and Textiles*, 5(1), 1–18. <https://doi.org/10.1186/s40691-018-0139-z>
 46. David Strohmaier, Jianqiu Zeng, Muhammad Hafeez (2019). Trust, distrust, and crowdfunding: A study on perceptions of institutional mechanisms. *Telematics and Informatics* 43 (2019) 101252

47. Bilos, A., Budimir, B. Understanding the Adoption Dynamics of ChatGPT among Generation Z: Insights from a Modified UTAUT2 Model. *J. Theor. Appl. Electron. Commer. Res.* 2024, 19, 863–879. <https://doi.org/10.3390/jtaer19020045>
48. Mohamed Merhi, Kate Hone, Ali Tarhini (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. *Technology in Society* 59 (2019) 101151
49. Artur Strzelecki (2025). ChatGPT in higher education: Investigating bachelor and master students' expectations towards AI tool. *Education and Information Technologies* (2025) 30:10231–10255 <https://doi.org/10.1007/s10639-024-13222-9>
50. Montathar Faraon, Kari Rönkkö, Marcelo Milrad, Eric Tsui (2025). International perspectives on artificial intelligence in higher education: An explorative study of students' intention to use ChatGPT across the Nordic countries and the USA. *Education and Information Technologies* <https://doi.org/10.1007/s10639-025-13492-x>
51. Hamzeh Moradi (2025). Integrating AI in higher education: Factors influencing ChatGPT acceptance among Chinese university EFL students. *International Journal of Educational Technology in Higher Education* (2025) 22:30 <https://doi.org/10.1186/s41239-025-00530-4>
- Cabero-Almenara, J., Palacios-Rodríguez, A., Rojas Guzmán, H.d.l.Á., Fernández Scagliusi, V. Prediction of the Use of Generative Artificial Intelligence Through ChatGPT Among Costa Rican University Students: A PLS Model Based on UTAUT2. *Appl. Sci.* 2025, 15, 3363. <https://doi.org/10.3390/app15063363>
52. Romero-Rodríguez, J., Ramírez-Montoya, M., Buenestado-Fernández, M., & Lara-Lara, F. (2023). (Romero-Rodríguez et al., 2023) 12(2), 323-339. doi: 10.7821/naer.2023.7.1458
53. Tribikram Budhathoki, Araz Zitar, Eric Tchouamou Njoya & Achyut Timsina (2024) ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT), *Studies in Higher Education*, 49:5, 831-846, DOI:10.1080/03075079.2024.2333937
54. Rashid, S. (2025). Habit Predicting Higher Education EFL Students' Intention and Use of AI: A Nexus of UTAUT-2 Model and Metacognition Theory. *Education Sciences*, 15(6), 756. <https://doi.org/10.3390/educsci15060756>
55. Benicio Gonzalo Acosta-Enriquez, Marco Agustín Arbulú Ballesteros, Olger Huamaní Jordan, Carlos López Roca and Karina Saavedra Tirado (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychology* (2024) 12:255 <https://doi.org/10.1186/s40359-024-01764-z>
56. Swathi A, Janani S, Satvik Vats, Selvanathan N, Shanmugapriya S and Alagarraja K (2025).
57. Emotionally Aware Artificial Intelligence Systems for Strengthening Global Human Connections and Enhancing Psychological Well Being. *Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research* 120, https://doi.org/10.2991/978-94-6463-718-2_48
58. Mohammed Nasiru Yakubu, Nakama David, Naima Hafiz Abubakar (2025). Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective. *Education and Information Technologies* <https://doi.org/10.1007/s10639-025-13441-8>
59. Abeer S. Almogren, Waleed Mugahed Al-Rahmi, Nisar Ahmed Dahri (2024). Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective. *Heliyon* 10 (2024) e31887
60. Nurul Aulia Ramadhina, Nurafni Rubiyanti, Rajiv Dharma Mangruwa (2022). The Influence of Performance Expectancy, Effort Expectancy, And Social Influence on Use Behavior with Behavioral Intention as A Mediator (A Case Study of Cash on Delivery (COD) System Users in Marketplaces). *International Journal of Social Science and Human Research* ISSN (print): 2644-0679, ISSN (online): 2644-0695 Volume 08 Issue 01 January 2025 DOI: 10.47191/ijsshr/v8-i1-24, Impact factor- 7.876 Page No: 215 – 224
61. Kim, Y., Blazquez, V., Oh, T. Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. *Behav. Sci.* 2024, 14, 1035. <https://doi.org/10.3390/bs14111035>

62. Selvi, M.S., Önem, S. Impact of Variables in the UTAUT 2 Model on the Intention to Use a Fully Electric Car. *Sustainability* 2025, 17, 3214. <https://doi.org/10.3390/su17073214>
63. Wang, Y., & Wang, Y. (2019). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 30(4), 619–634. <https://doi.org/10.1080/10494820.2019.1674887>
64. Hayes, Andrew F. 2018. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Second Edition. New York, NY: The Guilford Press.
65. Senali, M. G., Iranmanesh, M., Ismail, F. N., Rahim, N. F. A., Khoshkam, M., & Mirzaei, M. (2023). Determinants of intention to use e-wallet: Personal innovativeness and propensity to trust as moderators. *International Journal of Human–Computer Interaction*, 39(12), 2361–2373. <https://doi.org/10.1080/10447318.2022.2076309>
66. Devadas Menon, K Shilpa (2023). “Chatting with ChatGPT”: Analyzing the factors influencing users’ intention to Use the Open AI’s ChatGPT using the UTAUT model. *Heliyon* 9 (2023) e20962
67. Resam Lal Poudel, Chandra Kanta Bastakoti (2024). Impact of Behavioural Intention to Use Generative Artificial Intelligence on Academic Performance of Students in Higher Education Institutions. *Prithvi Journal of Research and Innovation [A Peer-Reviewed, Open Access Multidisciplinary Bilingual Journal; Indexed in NepJOL]* ISSN 2705-4888 [Print]; ISSN 2705-4896 [Online]; JPPS Star-Rated Journal Volume 6; 15 December 2024; pp. 1-21
68. Sneha Kandoth, Suraj Kushe Shekhar (2022). Social influence and intention to use AI: the role of personal innovativeness and perceived trust using the parallel mediation model. *Forum Scientiae Oeconomia* Volume 10 (2022) No. 3 DOI: 10.23762/FSO_VOL10_NO3_7
69. Seo, K.H., Lee, J.H. The Emergence of Service Robots at Restaurants: Integrating Trust, Perceived Risk, and Satisfaction. *Sustainability* 2021, 13, 4431. <https://doi.org/10.3390/su13084431>
70. Flavián, C., Pérez-Rueda, A., Belanche, D. and Casaló, L.V. (2021). “Intention to use analytical Artificial Intelligence in services. The effect of technology readiness and awareness”, *Journal of Service Management*. Forthcoming. DOI 10.1108/JOSM-10-2020-0378.
71. Li, X., Jiang, M.Y.-c., Jong, M.S.-y., Zhang, X.; Chai, C.-s. Understanding Medical Students’ Perceptions of and Behavioral Intentions toward Learning Artificial Intelligence: A Survey Study. *Int. J. Environ. Res. Public Health* 2022, 19, 8733. <https://doi.org/10.3390/ijerph19148733>
72. Qianli Wu, Jinyan Tian, Ziyang Liu (2025). Exploring the usage behavior of generative artificial intelligence: a case study of ChatGPT with insights into the moderating effects of habit and personal innovativeness. *Current Psychology* (2025) 44:8190–8203 <https://doi.org/10.1007/s12144-024-07193-w>
73. Ojo, AO, Alias, M, Dorasamy, M, Sarwar, A & Ojo, OT 2022, 'Moderating effects of opportunity on the Cognitive and Motivational Factors of Internet engagement: A Study of the digital divide in Malaysia', *International Journal of Technology and Human Interaction*, vol. 18, no. 1. <https://dx.doi.org/10.4018/IJTHI.299353>
74. Prensky, M. (2001). Digital natives, digital Immigrants. *On the Horizon*, 9(5), <https://www.marcprensky.com/writing/Prensky%20%20Digital%20Natives,%20Digital%20Immigrant%20-%20Part1.pdf>
75. Polyportis A (2024) A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education. *Frontiers in Artificial Intelligence*. 6:1324398. doi: 10.3389/frai.2023.1324398
76. Kooli, C. Chatbots in Education and Research: A Critical Examination of Ethical Implications and Solutions. *Sustainability* 2023, 15, 5614. <https://doi.org/10.3390/su15075614>
77. Zahir Osman, Bibi Nabi Ahmad Khan, Mohammad Naim Ismail, Yuzery Yusoff, Noral Hidayah Alwi, Khairul Hamimah Mohamad Jodi (2023). Artificial Intelligence Usage in Higher Education: Academicians' Perspective. *International Journal of Academic Research in Accounting, Finance & Management Sciences* Vol. 13, No. 4, 2023, E-ISSN: 2225-8329 © 2023