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Understanding Human–AI Interaction and Adoption in Higher Education: An Extended UTAUT2 Model of AI Literacy, Trust and Student Use Behaviour

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Abstract
Artificial Intelligence (AI) is rapidly transforming the educational landscape, yet students' perceptions and attitudes toward its adoption remain a crucial area of study. This research examines students' willingness to adopt AI tools in higher education using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. Data were collected from 400 engineering students across Tamil Nadu, India, through a structured questionnaire. The study employed advanced statistical analysis with specialized software to test hypotheses about students' behavioural intention and actual use of AI technologies. The findings reveal that key factors such as perceived usefulness, ease of use, and social influence significantly impact students' intention to adopt AI. Additionally, hedonic motivation (enjoyment), price value, and habit were found to play important roles in shaping both intention and actual usage behaviour. The results indicate that all these constructs collectively influence students' acceptance and continued use of AI in academic settings. This study contributes to the growing body of literature by focusing on AI adoption in a South Asian higher education context, which remains underexplored. It provides valuable insights for universities and policymakers to design effective strategies for integrating AI in a way that is inclusive, ethical, and sustainable. By understanding the factors that drive student adoption, institutions can enhance learning experiences and maximize the benefits of AI technologies. Overall, the study highlights the transformative potential of AI in education while emphasizing the need for user-centered and responsible implementation approaches.

Keywords: Artificial Intelligence in Education; UTAUT2; Behavioural Intention; Technology Adoption; Structural Equation Modeling; Higher Education; AI Tools

1. Introduction

In earlier times, education was mostly informal. Gurukuls prioritized comprehensive learning and skill development above formal education. They were unmonitored by the government and prioritized discussions, debates, and life skills over science and maths (Divya, 2022). Any post-secondary education, training, or research that a state's authorities acknowledge as a component of its higher education system is considered higher education, according to UNESCO. Academic, professional, technological, creative, and pedagogical education are all included in this (Higher Education: What You Need to Know | UNESCO, n.d.). According to Warren Bennis, "leadership is the ability to turn vision into reality." Educational leadership in the twenty-first century needs to be up to date in order to deal with concerns of the digital age. The way that schools teach is starting to shift (Kaur, 2023). In the twenty-first century, artificial intelligence has become an essential component of learning settings and is not a new concept in education (Chen et al., 2022; Ouyang & Jiao, 2021). Adaptive learning platforms, intelligent tutoring systems, predictive analytics, and generative AI tools are examples of AI-driven technologies that have revolutionized pedagogy by replacing standardised instruction with data-driven customization (Crompton & Burke, 2024; Garzón et al., 2025). According to Ifenthaler et al. (2024), artificial intelligence (AI) not only improves the effectiveness of instruction but also transforms the basis of learning by impacting the creation, validation, and preservation of information throughout time.

From a sustainability standpoint, education encompasses more than just achieving high grades; it also entails the development of cognitive skills, equal access, long-term information retention, and the capacity to continue learning throughout one's life. AI could improve adaptive learning methods and facilitate quicker access to resources. This is in line with Sustainable Development Goal 4 of the UN, which is to deliver high-quality education (Salas-Pilco et al., 2022). UNESCO cautions that there are systemic hazards associated with integrating AI into education. Bias in algorithms, difficulties with data management, an excessive reliance on technology for instruction, and the growing divide between those with and without access to digital tools are some of the main issues with employing AI in education. Recent research from 2024 by Ifenthaler et al. and the American Psychological Association provides evidence of this. These problems raise the question of whether AI will actually improve education and make it more sustainable or if it will only make matters worse.

According to recent research, AI improves short-term academic performance and personalisation, but its long-term effects on critical thinking, self-regulated learning, and cognitive autonomy are still up for debate (Garzón et al., 2025; Zawacki-Richter et al., 2019). This disparity emphasises the necessity of moving away from descriptive evaluations and toward analytical investigations into learners' viewpoints, internalisation procedures, and the long-term advantages of AI-enhanced learning environments. Theoretically, frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Technology Acceptance Model (TAM) have provided a comprehensive explanation of the integration of technology in education (Venkatesh et al., 2012). Four primary elements were found to influence people's intention to use and adopt information technology in the previous UTAUT model (UTAUT1), created by Venkatesh et al., 2003 (Nikolopoulou & Zacharis, 2023). These consist of social influence, performance expectancy, effort expectancy, and enabling circumstances. (Venkatesh et al., 2012) created the UTAUT2 model by incorporating three more characteristics into the UTAUT1 model: price value, habit, and hedonic motivation. The suggested model has been expanded to include trust and AI literacy as extra dimensions, strengthening the explanatory breadth of this study and capturing the complex behavioural and cognitive elements that affect students' adoption of technology. According to these theories, behavioural intention and actual usage are strongly influenced by perceived utility, simplicity of use, social impact, and facilitating factors. Higher education research has made extensive use of the UTAUT2 model, which demonstrates how factors such as hedonic motivation, performance expectation, effort expectancy, and enabling conditions affect faculty and student adoption and usage of digital technology (Acosta-Enriquez et al., 2024). However, a large portion of the work now in publication assesses AI primarily in terms of adoption intents or performance outcomes, frequently ignoring its function in fostering long-term learning. Furthermore, there is little empirical study on learners' lived experiences, cognitive engagement, and the sustainability of the abilities they acquire; instead, most studies concentrate on particular institutions or technologies. One popular approach for researching how people accept new technology is the Technology Acceptance Model (TAM). Numerous studies examine users' intentions to embrace or use technology as well as their actual usage behaviours using this core model and its extensions (TAM2, TAM3, UTAUT, and UTAUT2) (Hutchins & Hook, 2017). Curriculum modifications and instructional strategy improvements are essential for meaningful integration in order to give students and teachers the 21st-century abilities they need. This study investigates how artificial intelligence affects educational learning outcomes using a learner-centred analytical methodology. Through primary data gathering, the study evaluates how AI integration affects learning efficacy, engagement, skill retention, and long-term educational advantages. The Anna University South Zone in Tamil Nadu, India, a developing nation, is the subject of this study. This study aims to investigate whether trust and AI literacy significantly predict students' behavioural intention to adopt AI technologies for learning, whether habit directly influences use behaviour, whether behavioural intention strongly predicts actual use behaviour of AI tools among students, and how performance expectancy and effort expectancy affect students' behavioural intention to adopt and continue using AI tools in higher education. It also evaluates how hedonic motivation and price value shape students' behavioural intention to use AI tools for academic purposes.

The following are the research questions (RQs) that direct this investigation.

RQ1: Do students' behavioural intentions to embrace and continue utilising AI tools in higher education depend significantly on achievement expectancy and effort expectancy?

RQ2: How do price value and hedonic motivation influence students' behavioural intention to utilize AI tools for academic purposes?

RQ3: How much do social influence and enabling circumstances impact students' intention and actual use of AI tools?

RQ4: Are students' behavioural intentions to use AI devices for learning significantly predicted by trust and AI literacy?

RQ5: Does behavioural intention significantly predict students' actual usage of AI technologies, and does habit directly affect use behaviour?

2. Literature review and theoretical framework

This study is theoretically grounded in the UTAUT2 model, which includes seven constructs. This model, which was created by Venkatesh et al. (2003) as an improvement on the previous UTAUT model (UTAUT1), has four essential elements that have the greatest impact on technology adoption (Nikolopoulou & Zacharis, 2023). These elements include social influence, performance expectancy, effort expectancy, and enabling circumstances. He then added three more elements to the model, which together make up the UTAUT2 model: price value, hedonic incentive, and habit. This study model has been further enhanced by adding the variables of trust and AI literacy, building upon its fundamental framework. Researchers frequently employ models like UTAUT1 and UTAUT2 to better understand how individuals accept and use technology, particularly in educational contexts. Numerous researches, such as those by Al-Fraihat et al. (2020), Farooq et al. (2017), and J. A. Kumar & Bervell (2019), have employed these models to investigate how instructors and students embrace and utilise technology in higher education. In particular, the UTAUT2 model has been evaluated in a variety of settings, such as online gambling, mobile banking, and online banking. For example, it was applied to online banking in 2018 by (Owusu Kwateng et al., 2019) and internet and mobile banking in 2015 by (Arenas Gaitán et al., 2015). In 2019, (Ramírez-Correa et al.) employed the model to study online gambling, and in 2021, (Gansser & Reich, 2021a) investigated its use in artificial intelligence. It's interesting to note that earlier research has demonstrated the value of the UTAUT2 model for examining how individuals embrace e-learning tools (Lahrash et al., 2021). The model's creators urge scholars to keep investigating and bolstering this idea in a variety of settings, technology, and user demographics. To better understand how people utilize technology, it is crucial to look into and validate this idea, as stated by Nikolopoulou and Zacharis (2023). The UTAUT model is still applicable today since it is frequently used to research technology adoption, particularly when it comes to comprehending how students use AI in the classroom. AI-backed technologies like learning management systems, intelligent tutoring programs, and generative AI platforms are projected to be used in schools today by both teachers and students. Both teachers and students can learn more easily in mixed learning environments thanks to this technology. Even while AI is employed in in-person instruction, it could not be as common as in entirely online environments. But as Saleem et al. (2025) point out, AI is becoming more and more significant in education, and it's critical to comprehend how teachers and students embrace and utilize these technologies. Researchers can better understand how individuals accept and use technology by employing models such as UTAUT1 and UTAUT2, ultimately improving teaching and learning.

2.1 Empirical studies

A UTAUT-based study on students' adoption of AI in Indian higher education institutions was carried out by (M. Kumar et al., 2025). The findings demonstrated that while effort expectancy and social influence have less of an effect on behavioural intention, performance expectancy and enabling surroundings do. Teachers' opinions of AI were also investigated using the UTAUT framework (Faculty of Education, Universiti Kebangsaan Malaysia (UKM), Bangi, Malaysia & Kamsin, 2025). Performance expectancy and social influence were not major predictors of behavioural intention, but effort expectation and AI fear were found to have a substantial impact. (Ali et al., 2018) used structural equation modelling to evaluate e-learning systems, emphasising that enhancing academic performance and learning outcomes depends on students' acceptance and efficient usage of these systems. The causes of perceived ease of use in online learning were examined by Huang et al. (2022). They discovered that perceived enjoyment, computer self-efficacy, and external control had a significant impact on perceived ease of use, which in turn influences the adoption of technology. (Adewale et al., 2024) carried completed extensive research showing that the use of AI in education greatly improves academic success, learning outcomes, and personalized learning.

(Xu et al., 2024) used the UTAUT2 model with a sample of 402 respondents to investigate the use of AI tools among Chinese university teachers. The findings demonstrated that whereas facilitating factors, habit, and behavioural intention strongly predict actual usage behaviour, performance expectancy, effort expectancy, and hedonic incentive considerably influence behavioural intention. Interestingly, habit was the most essential element in predicting usage behaviour, and effort anticipation was the most critical factor in defining behavioural intention. In a different empirical study, Grassini et al. (2024) used the UTAUT2 paradigm to examine AI acceptance among Norwegian university students. According to the study, behavioural intention is primarily determined by performance expectancy, which is followed by habit. This highlights the critical role that perceived utility and consistent use play in the adoption of AI. Some intriguing findings have come from studies on the application of new technology, such as mobile learning tools and artificial intelligence. For instance, a study by Sergeeva et al. (2025) looked at the adoption of generative AI technology by students in higher education. To determine what influences this adoption, they employed a model known as UTAUT2. They discovered that students' use of AI is significantly influenced by their behaviours. Additionally, pupils are more willing to employ AI if they believe it will improve their performance. Additionally, students' intentions to utilise AI can be positively impacted by their enjoyment of the experience, their perception of its economic value, and their influence from others. But the study also revealed that the adoption of AI can occasionally be hampered by current support systems, indicating that institutions need to make improvements in this area. Another study by Ke et al. (2025) investigated the impact of AI literacy on Chinese university students' adoption of AI. To identify the variables at work, they integrated AI literacy with the UTAUT dimensions. The findings demonstrated that students' intentions to employ AI might be greatly influenced by their comprehension of the technology. This purpose can be mediated by a number of factors, including the expectation that AI will enhance performance, the ease of use of AI, and the influence of social circles. However, the choice to employ AI in this situation did not appear to be directly influenced by the resources and assistance that were available. Additionally, a study (Lai et al., 2022) examined the adoption of mobile-assisted language learning technologies by students in higher education. The study, which used a modified version of the UTAUT framework, discovered that students are more likely to utilise these tools if they think they would improve their learning and if they have a favourable attitude toward them. The complexity of factors impacting technology adoption is shown by the fact that students' use of these tools is not immediately impacted by the context in which they are employed. In order to investigate the uptake of 5G technology, Mustafa et al. (2022) extended the UTAUT2 model outside schooling. With a large number of participants, they employed a hybrid approach. The results showed that a number of factors greatly influence the intention to use 5G, including the assumption that 5G will improve performance, the enjoyment of using 5G, having the required support, creating habits, and seeing the value in 5G. Furthermore, there is a high correlation between the intention to use 5G and the actual use of it. However, being influenced by others had little effect in this situation, indicating that when it came to embracing new technologies like 5G, individual convictions and experiences may take precedence over societal influences.

In a recent study, Singh et al. (2025) used the UTAUT2 model to investigate ChatGPT uptake among higher education students in Punjab, India. The study, which used data from 313 students, discovered that while effort expectancy had no significant impact on behavioural intention, performance expectancy, social influence, hedonic incentive, habit, and facilitating factors did. Furthermore, real ChatGPT usage was strongly influenced by behavioural purpose and habit. In a similar vein, (Gansser & Reich, 2021b) used an enhanced UTAUT2 model to investigate AI product adoption in a large-scale empirical survey with 21,841 respondents. Their findings demonstrated the resilience of UTAUT2 in AI-related scenarios by showing that the majority of UTAUT2 constructs, along with other variables like convenience and personal innovativeness, significantly explained behavioural intention and usage behaviour. Using an integrated TPB, TAM, and UTAUT paradigm, 2,894 university students' adoption of AI was examined in higher education (A Systematic Review of AI Adoption in Higher Education, 2026; Nurtanto et al., 2025). The results showed that while perceived risk had a negative effect on behavioural intention and results, attitude, performance expectancy, enabling conditions, and behavioural intention all had a substantial impact on student performance. Dečman (2015), who investigated e-learning adoption in an obligatory higher education setting, offers additional empirical evidence. The study supported the applicability of the UTAUT model in educational contexts by confirming that students' intention to use e-learning systems is highly influenced by performance expectancy and social influence. The UTAUT2 model was used in a different study by Rudhumbu (2022) to examine university students' adoption of blended learning. The results showed that behavioural intention, which in turn had a considerable impact on actual usage, was positively influenced by performance expectancy, effort expectancy, social influence, enabling conditions, and hedonic incentive. In a similar vein, Wu et al. (2022) used the UTAUT model in conjunction with perceived risk theory to investigate students' readiness to accept AI-assisted learning environments. The results showed that while psychological risk had a negative impact on adoption, performance expectancy, effort expectancy, and social influence had a favourable impact on students' willingness. Additionally, 185 college students in Erode, Tamil Nadu participated in an empirical study carried out by (Dr. G. Sakthivel & Devi, 2024). The study, which used statistical methods like ANOVA, discovered that while awareness and access problems still exist, AI technologies greatly improve student engagement, personalised learning, and academic accomplishment.

Researchers have discovered that a number of factors significantly influence people's intents and behaviours when it comes to embracing new technologies. For example, a study on mobile learning by Chao (2019) found that a person's perception of a technology's performance, ease of use, satisfaction, and level of trust all significantly influence whether or not they will actually utilise it. However, people are less likely to use the technology if they believe it poses a risk. In a similar vein, (Strengths and Weaknesses of Online Learning, n.d.) examined the factors that influence students' performance in e-learning and discovered that the opinions of their peers, the ease with which they can obtain the resources they require, and the ease of use of the technology all play a significant role. Surprisingly, though, they discovered that in this situation, the technology's performance wasn't that important. Using an updated version of the UTAUT model, another study on mobile marketing by Eneizan et al. (2019) discovered that performance, simplicity of use, social influence, how simple it is to obtain the technology, habit, and risk all affect people's intentions to use the technology. This supports the notion that these elements are crucial for many kinds of technology adoption research. When it comes to AI tools in education, Faraon and colleagues conducted a large study in multiple countries and discovered that factors such as how well the tools' function, how fun they are to use, how frequently people use them out of habit, and what other people think all have a great impact on whether or not students desire to use them. Crucially, actual usage is strongly predicted by habit and desire to use. According to (J. A. Kumar & Bervell, 2019), habit, enjoyment, and performance expectancy are important factors influencing intention to use Google Classroom, with habit being the best predictor of whether or not students actually utilise it. These same factorsperformance expectancy, effort expectancy, social influence, and conducive conditionswere found to be significant in predicting students' adoption of learning management systems back in 2012 (Fidani & Idrizi, 2012). This demonstrates the continued significance of technology in raising productivity and academic results. All of these studies highlight the intricate interactions between various elements that affect technology adoption, ranging from social influences and individual habits to the technology's functionality and ease of use. Developers and educators can produce technologies that are more likely to be embraced and utilised successfully by taking these variables into consideration. Furthermore, the robustness of the UTAUT model in forecasting technology adoption behaviours is highlighted by the similar results across many research and technologies. This can direct the creation of tactics to encourage the use of new technologies in classrooms, ultimately improving instruction and learning opportunities. In conclusion, even though the details may differ depending on the situation, the general picture is evident: a variety of factors, including both internal and external components, have an impact on technology adoption. An atmosphere that facilitates the successful integration of technology into teaching methods can be created by identifying and resolving certain issues.

2.2 Hypothesis Development

Based on UTAUT-2 and the identified gaps in learners'behavioural intention to use AI in education, the following hypotheses are proposed:

2.2.1 Performance Expectancy

The degree to which an individual thinks a system will improve their performance is known as performance expectancy (PE) (Venkatesh et al., 2003; Zwain, 2019). It is the main driving force behind people's adoption and continued use of a particular technology. Due to variations in study conditions, methodology, and sample sizes, the connection between PE and BI has changed across various contexts (Ali et al., 2018). Students have learnt how to employ AI technologies to enhance their academic performance and increase their level of engagement as they become more prevalent in higher education.

H1: Performance expectancy positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.2 Hedonic Motivation

People can feel content and joyful when they use technology. The enjoyment and optimistic outlook that come from utilising a computer or phone is known as hedonic motivation (Venkatesh et al., 2012). Scholars have been researching this concept and believe it is crucial to comprehend how it impacts students' academic performance. Although several studies have already examined this, more investigation is required to determine the true extent of the impact. According to one study, for instance, hedonic motivation has a significant role in people's attitudes toward technology and can affect how much they enjoy using it (Alalwan et al., 2017; Megadewandanu et al., 2016, as quoted in TheoryHub, n.d.). According to a different study, hedonic drive may even have an impact on students' academic performance. Therefore, it's crucial to continue investigating how we can use technology to enhance the effectiveness and enjoyment of learning.

H2: Hedonic motivation positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.3 Habit

After studying and utilising technology extensively, habits demonstrate the extent to which people carry out tasks automatically. It illustrates how ingrained technology use has become in people's everyday lives (Venkatesh et al., 2012). This idea expands upon the automaticity perspective, which holds that repetitive use of technology eventually becomes unconscious and independent of reason rather than the product of conscious assessment each time, as previous models like the Theory of Planned Behaviour claimed (Limayem et al., 2007).

H3: Habit positively influences learners' use behaviour in adopting and continuing to use Artificial Intelligence (AI) tools for learning in higher education.

2.2.4 Facilitating conditions

Having the appropriate tools is essential when utilising technology in the classroom. Zacharis and Nikolopoulos referred to this as "facilitating conditions" in their paper from 2022. In essence, it refers to having sufficient institutional resources and infrastructure to facilitate the application of technology. For students, this involves having access to personal computers, high-speed internet, Wi-Fi, and labs equipped with the required tools. Technical assistance and competence with the current technologies are also crucial.

Together, these elements produce an atmosphere that facilitates the efficient use of technology in education. The availability of these tools can significantly impact students' ability to use technology for learning, as observed by Tarhini et al. (2014).

H4: Facilitating conditions positively influence learner's behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.5 Price value

People analyse the benefits and drawbacks of a new technology before deciding to use it. It involves determining whether the advantages of utilising it outweigh the expenses. Researchers like Venkatesh and others (Raman et al., 2022) have discovered that individuals typically select technologies that they believe will have more advantages than disadvantages. In particular, students prefer inexpensive and practical technology that will improve their learning or make their lives easier.

H5: Price value positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.6 Social influence

According to Venkatesh et al. (2003), social influence is the extent to which a person feels that significant others, such as family, friends, or teachers, think they should utilise a specific technology. Numerous studies have shown that social influence positively affects our intention to use specific technology in a learning environment, such as multimedia tools and educational management systems. It has usually been demonstrated that social influence, which encompasses the impact of friends, family, coworkers, and social media, favourably affects behavioural intention (Akturan & Tezcan, 2012; Venkatesh et al., 2012). For instance, children are more likely to desire to utilise these technologies if their classmates, teachers, or role models encourage their use. Numerous studies conducted over the years have demonstrated this, finding a high correlation between social impact and behavioural intentions to adopt new technology (Venkatesh et al., 2003).

H6: Social influence positively influences learners' use behaviour in adopting and continuing to use Artificial Intelligence (AI) tools for learning in higher education

2.2.7 Effort Expectancy

The term "effort expectancy" (EE) describes how simple and easy a system is to use (Venkatesh et al., 2003). People assume that a system will be easy to use and understand (Rudhumbu, 2022). Adoption of new technologies is significantly influenced by EE. Additionally, it facilitates students' quicker adoption of new technologies (Huang et al., 2022). According to Venkatesh et al. (2003), effort expectancy is conceptually based on the perceived ease of use and complexity constructs from the Technology Acceptance Model. It represents the amount of mental and physical work a user anticipates a system will require. It covers elements like a system's adaptability, simplicity of learning, and interface design, which is especially important for students using AI technologies for the first time.

H7: Effort expectancy positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education

2.2.8 Trust

Efficiency, effective personalised learning, the capacity to modify teaching strategies to improve educational outcomes, and the potential to improve students' problem-solving abilities have all been considered when evaluating trust in AI in education. faith is an important but little-researched factor influencing whether and how people decide to integrate AI into their operations since ethical issues and ambiguities often undermine faith in this technology. Fairness, algorithmic bias, and transparency are frequent ethical issues with AI in education; reliable AI necessitates consideration of data privacy, security, and bias mitigation (Borenstein & Howard, 2021; Vincent-Lancrin & van der Vlies, 2020; Chai et al., 2020).

H8: Trust positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.9 AI Literacy

Researchers and educators have concentrated on AI literacy in education to prepare students and all citizens to live and work safely and effectively with AI. (Ng et al., 2021) divide AI literacy into four categories: knowledge and comprehension of AI, application of AI, assessment and development of AI, and AI ethics (Grassini, 2023). Building on this basis, further tools like the Meta AI Literacy Scale have operationalised these domains into quantifiable subjective evaluations, putting them with psychological elements like self-efficacy in handling AI as the "basic" AI literacy aspects.

H9:AI Literacy positively influences learners' behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education.

2.2.10 Behaviour intention and use behaviour

The motivation behind the adoption of a certain technology or system is known as behavioural intention (BI). Use behaviour, on the other hand, reflects how that system or technology is actually used (Venkatesh et al., 2003). There is a strong correlation between behavioural intention (BI) and usage behaviour (USEB) in technology-enabled learning environments, according to earlier research (Azizi et al., 2020; S. A. Raza & Hanif, 2013). Fundamentally, the UTAUT model emphasises the theoretical premise that intention precedes and propels actual usage by treating behavioural intention as the primary predictor of technology use behaviour. The initial UTAUT model showed that its dimensions account for up to 70% of the variance in behavioural intention, making this relationship one of the strongest in technology-acceptance studies (Venkatesh et al., 2003).

H10: Behavioural intention positively influences learners' use behaviour in adopting and continuing to use Artificial Intelligence (AI) tools for learning in higher education.

3. Proposed Methodology

3.1 Research model

This study explores the factors that positively impact learners'behavioural intention to adopt and continue using Artificial Intelligence (AI) tools for learning in higher education. The conceptual model is displayed in Figure 1 below. The model incorporates factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, trust and AI literacy that influence behavioural intentions, which, in turn, shape how students use these tools.

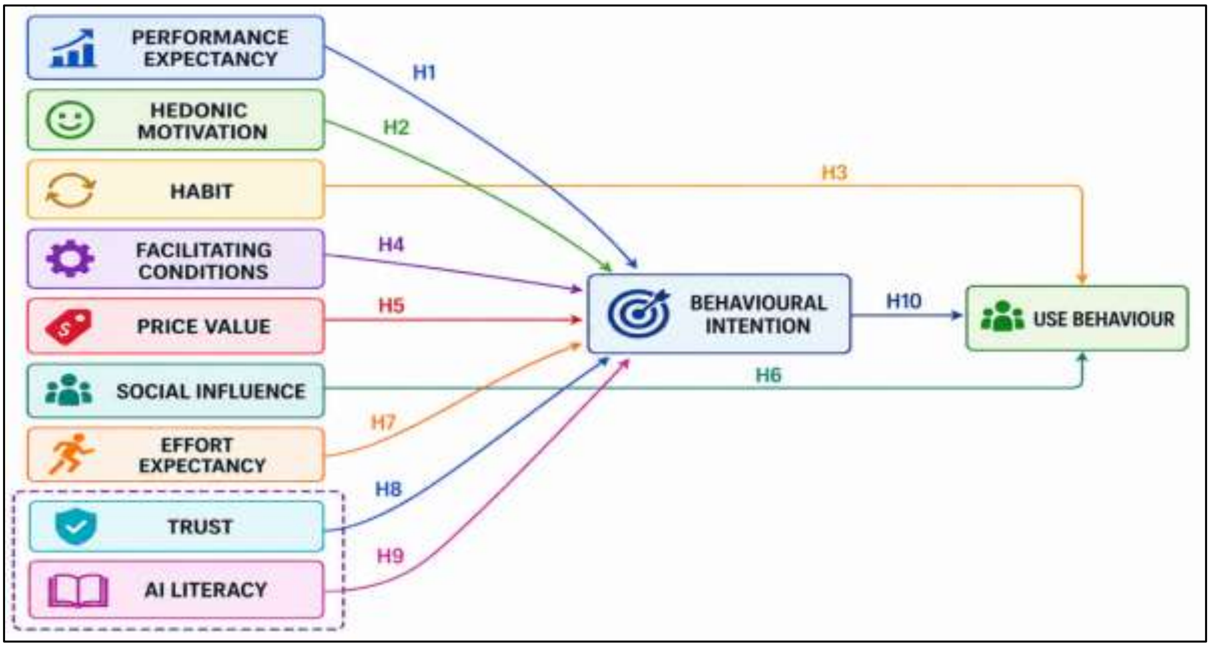

Figure 1: Conceptual Model of the proposed study: Research model and hypotheses

3.2 Data collection method and measurement instrument

This study employed a quantitative research approach, collecting data via a questionnaire administered to students at a regional university. Data were gathered using non-probability sampling methods, including convenience sampling. The survey link was emailed to both undergraduate and postgraduate engineering students ofAnna University South Zone of Madurai in Tamil Nadu, India. A total of 400 participants responded to the study, which was conducted in February and March of 2026. A questionnaire took about 7 minutes to complete. It used a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5), with 3 to 6 scale items. The measurement elements for Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HB),Social Influence (SI),Trust(T),AI Literacy(AIL), Behavioural Intention (BI), and Use Behaviour (UB) in the UTAUT2 model are based on previous studies (Hoi, 2020; Sitar-Taut & Mican, 2021; Venkatesh et al., 2003, 2012; Zwain, 2019; Al-Fraihat et al., 2020; Farooq et al., 2017; Mehta et al., 2019).

Behavioural intention serves as a mediator, enabling the indirect effects of H1-H9 on use behaviour, except for habit and social influence (H3 and H6), which directly affect use behaviour. This suggests that people may use technology unintentionally, simply because it is part of their routine or due to social pressure. Finally, H8 highlights the most significant relationship: behavioural intention leads to actual use behaviour. After establishing the theoretical concepts of the factors involved in the literature review, the study assesses reliability using reliability analysis and confirmatory factor analysis. To verify validity, the research hypotheses were tested through linear regression and path coefficient analysis.

3.3 Statistical technique

This research uses specialized software, SPSS (v.21) and AMOS(v.23), to analyze data and test ideas. These programs help us understand how different variables are related to each other. A method called CB-SEM (Covariance-based Structural Equation Modeling)is used in this study to test hypotheses and examine how factors influence one another. This method is particularly effective for developing and expanding ideas, especially when secondary and tertiary components are involved. Some researchers, like Astrachan et al., found that this method helps to understand cause-and-effect relationships more clearly. AMOS is used to check the UTAUT2 model, but CB-SEM is a better approach. This approach helps us develop scales, explore and confirm our findings, evaluate the importance of hidden factors, and analyze cause-and-effect relationships. Structural Equation Modeling (SEM) was chosen, as done by Ali et al., instead of other statistical methods. This choice was made because SEM is considered a powerful tool for understanding complex relationships between variables. By using SEM, a clearer understanding of how different factors interact with each other can be obtained, thereby enabling more informed decisions to be made.

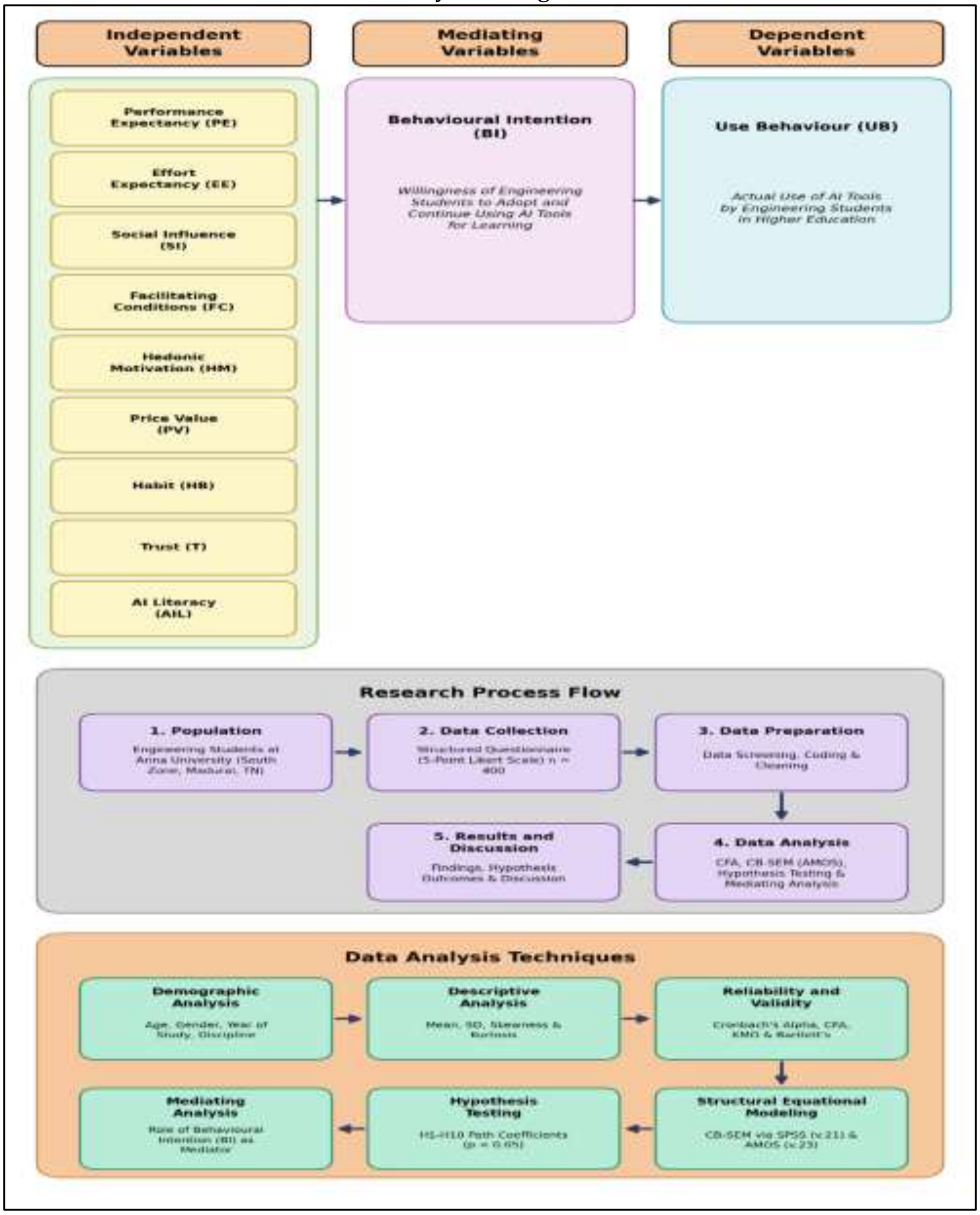

Figure 2: Research Design Overview: Study Variables, Data Collection Process, and Analytical Techniques

3.4 Demographics

Table 1 shows the demographic details of the study sample. The sample includes 400 people, with slightly more men (51.5%) than women (48.5%), indicating nearly equal gender distribution. Most respondents are aged 18 to 21 (57.4%), followed by those aged 22 to 26 (41.8%). Only a small percentage (0.8%) is between 26 and 30, suggesting the sample is mainly young. The majority of participants are undergraduate students (58.5%), while 41.5% are postgraduate students. Now, when it comes to the sample size, some researchers like (Román & Iacobucci, 2010)say that 50-100 people are enough for certain types of analysis.(White, 2022)think that a sample size of 50 is a bit weak, 300 is good, 500 is very good, and 1000 is excellent. This proposed study includes 400 students, which puts us squarely in the good-to-very good range, indicating a high level of confidence in the results.

Table 1: Demographic Profile of the Respondents

Demographic variable	N	%
Gender		
Male	206	51.5
Female	194	48.5
Age		
18-21	230	57.4
21-26	167	41.8
26-30	3	0.8
Academic Level		
Under Graduate	234	58.5
Post Graduate	166	41.5

4. Data Analysis and Findings

4.1 Preliminary analysis

Before data analysis, any missing information or unusual values are checked. A statistics program called SPSS, version 25, is used to see how often certain values appeared. No missing or mistyped values were found.

According to(Yusoff et al., 2025), Kaiser-Meyer-Olkin (KMO) and Bartlett's test evaluate sampling adequacy and variable homogeneity. KMO should be above 0.50, and Bartlett's test should be statistically significant. As shown in Table 2, the KMO value is 0.903, and Bartlett's test is significant ($p < 0.001$), confirming that the correlation matrix is suitable for factor analysis.

To assess whether the data follow a normal distribution, two key measures are used: skewness and kurtosis. For data to be considered normal, skewness should be between -2 and +2, and kurtosis should be between -7 and +7. As shown in Table 3, the skewness ranged from -1.308 to 0.566, and the kurtosis from -1.020 to 1.830, which suggests that the data are indeed normal. To ensure that the data did not have a problem called multicollinearity, where some variables are too closely related to each other, the Variance Inflation Factor (VIF) and tolerance values are calculated. The VIF scores are between 0.000 and 0.835, and the tolerance values are between -2.707 and 4.302. These values confirm that there is no multicollinearity issue in the data. Research by Fisher (1993) found that using a specific type of survey scale, with a certain number of questions, and making the survey anonymous and online can help reduce a problem called social desirability bias. This is when people answer questions in a way they think is socially acceptable, rather than honestly. By following this approach, participants can provide more accurate and truthful responses. More details about VIF and tolerance scores can be seen in Table 4.

Table 2 Assessment of Sampling Adequacy and Sphericity for Factor Analysis (KMO and Bartlett's Test)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.903
Bartlett's Test of Sphericity	Approx. Chi-Square	3233.292
	df	55
	Sig.	.000

Table 3: Descriptive Statistics and Normality Assessment of Study Variables (Skewness and Kurtosis)

	N	Min	Max	Mean	SD	Skewness		Kurtosis	
	Stat	Stat	Stat	Stat	Stat	Stat	Std. Err	Stat	Std. Err
PE1	400	1	5	4.03	1.072	-1.269	.122	1.199	.243
PE2	400	1	5	3.95	1.026	-1.210	.122	1.372	.243
PE3	400	1	5	4.12	.953	-1.308	.122	1.830	.243
PE4	400	1	5	3.99	.972	-1.144	.122	1.447	.243

PE5	400	1	5	3.99	.927	-.999	.122	1.079	.243
PE6	400	1	5	4.07	.938	-1.068	.122	1.135	.243
HM1	400	1	5	3.94	.997	-.999	.122	.871	.243
HM2	400	1	5	3.92	.961	-.985	.122	1.050	.243
HM3	400	1	5	3.88	.975	-.993	.122	1.049	.243
HM4	400	1	5	3.82	.974	-.817	.122	.533	.243
HM5	400	1	5	3.90	.912	-.908	.122	.894	.243
HB1	400	1	5	3.96	.950	-1.042	.122	1.124	.243
HB2	400	1	5	3.93	.888	-.871	.122	.935	.243
HB3	400	1	5	3.99	.981	-.947	.122	.644	.243
FC1	400	1	5	2.62	.956	.362	.122	.083	.243
FC2	400	1	5	2.56	.974	.566	.122	-.052	.243
FC3	400	1	5	2.78	1.035	.420	.122	-.119	.243
PV1	400	1	5	3.79	.936	-.776	.122	.654	.243
PV2	400	1	5	3.78	.864	-.875	.122	1.300	.243
PV3	400	1	5	3.82	.889	-.643	.122	.401	.243
PV4	400	1	5	3.89	.888	-.981	.122	1.400	.243
PV5	400	1	5	3.89	.918	-.879	.122	.963	.243
SI1	400	1	5	3.80	.930	-.836	.122	.876	.243
SI2	400	1	5	3.79	.979	-.697	.122	.059	.243
SI3	400	1	5	3.61	1.120	-.665	.122	-.245	.243
EE1	400	1	5	3.81	.906	-.632	.122	.363	.243
EE2	400	1	5	3.94	.849	-.647	.122	.463	.243
EE3	400	1	5	3.99	.926	-1.018	.122	1.212	.243
BI1	400	1	5	3.95	.930	-.934	.122	.915	.243
BI2	400	1	5	4.02	.919	-.941	.122	.841	.243
BI3	400	1	5	4.02	.912	-1.026	.122	1.176	.243
BI4	400	1	5	4.00	.827	-.957	.122	1.449	.243
BI5	400	1	5	4.01	.871	-.984	.122	1.336	.243
UB1	400	1	5	3.99	.923	-.989	.122	1.090	.243
UB2	400	1	5	4.03	.916	-1.136	.122	1.575	.243
UB3	400	1	5	4.01	.904	-.900	.122	.684	.243
UB4	400	1	5	4.07	.882	-1.075	.122	1.454	.243
UB5	400	1	5	4.11	.931	-1.180	.122	1.374	.243
TR1	400	1	5	2.81	1.074	-.001	.122	-.567	.243
TR2	400	1	5	2.68	1.116	.167	.122	-.664	.243
TR3	400	1	5	3.09	1.167	.180	.122	-1.020	.243
AIL1	400	1	5	3.82	.890	-.592	.122	.320	.243
AIL2	400	1	5	3.90	.852	-.531	.122	.127	.243
AIL3	400	1	5	3.97	.891	-.834	.122	.843	.243
Valid N (listwise)	400								

Table 4: VIF and Tolerance score

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.594	.145		4.090	.000
PE_AVERAGE	.071	.041	.081	1.735	.084
HM_AVERAGE	.119	.047	.133	2.559	.011
HB_AVERAGE	.118	.043	.130	2.779	.006
FC_AVERAGE	-.068	.025	-.084	-2.707	.007
PV_AVERAGE	.195	.045	.199	4.302	.000
SI_AVERAGE	.132	.035	.153	3.729	.000
EE_AVERAGE	.313	.088	.332	3.559	.000
TR_AVERAGE	.004	.021	.006	.209	.835
AIL_AVERAGE	-.029	.087	-.029	-.328	.743

4.2 Reliability and Validity

Cronbach's alpha scores show that each part of the study is internally consistent. The scores are high, which means the study is reliable. All the scores are above 0.7, which is a good thing. The Cronbach's alpha values are 0.852 for PE, 0.851 for HB, 0.850 for PV, 0.857 for SI, 0.851 for EE, 0.848 for HM, 0.890 for FC,0.891 for TR, 0.886 for AIL, 0.848 for BI, and 0.851 for UB. As Van Griethuijsen and others found out in 2015, high internal reliability is important for a study to be taken seriously. In this case, the study seems to be quite strong. The different parts of the study all have high scores, which shows that they are all consistent and reliable.

The results also showed that the validity of the data was good, with a measure called average variance extracted being more than 0.5. This is important because it means that the data is consistent and reliable. Another measure, called CriticalRatio (CR), is also high, with ratings above 0.60, which is a good sign. The findings can be seen in Table 5.

Table 5: Validity analysis

	CR	AVE	MSV	ASV	PE	HM	HB	FC	PV	SI	EE	TR	AIL
PE	0.91	0.64	0.672	0.296	**0.800**								
HM	0.90	0.64	0.721	0.358	0.820	**0.797**							
HB	0.79	0.55	0.721	0.408	0.793	0.849	**0.741**						
FC	0.89	0.73	0.075	0.042	0.175	0.201	0.152	**0.855**					
PV	0.88	0.59	0.639	0.427	0.659	0.720	0.797	0.274	**0.768**				
SI	0.78	0.54	0.666	0.426	0.604	0.687	0.591	0.236	0.713	**0.731**			
EE	0.82	0.60	1.359	0.579	0.645	0.693	0.768	0.162	0.764	0.815	**0.774**		
TR	0.91	0.77	0.009	0.004	0.072	0.071	0.039	0.093	0.045	0.006	0.055	**0.875**	
AIL	0.80	0.57	1.359	0.501	0.622	0.691	0.754	0.152	0.759	0.796	1.166	0.068	**0.754**

Note: Boldfaced diagonal scores are the square root of AVE. Abbreviations: PE- Performance Expectancy, EE- Effort Expectancy, SI- Social Influence, FC- Facilitating Conditions, HM- Hedonic Motivation, PV- Price Value, HB- Habit, TR- Trust, and AIL- AI Literacy.

4.3 Confirmatory factor analysis

To check if the measurement model is working well, a special analysis called confirmatory factor analysis is used. The results showed that the model is a good fit, based on several key statistics: the chi-squared statistic is 4820.304, with 8degrees of freedom, and a p-value of less than 0.001. The ratio of the chi-squared statistic to the degrees of freedom is, which is a good sign. Other important numbers, such as the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI)is 0.879, and Adjusted Goodness of Fit Index (AGFI) is 0.778, which means the model is a good representation of the data. The Goodness of fit index (GFI)is 0.808, and the Root Mean Square Error of Approximation (RMSEA)is 0.070, which is less than 0.08, indicating a good fit. These numbers are based on guidelines from (Hair et al., 2006) and (Schmitt, 2011). All of this suggests that the extended model is a good predictor of how likely university students are to use and keep using Artificial Intelligence technologies in their studies. The relationships between the different parts of the model are then tested to see if they are as expected.

The structural model is tested by examining each standardized path that matches the hypotheses. As shown in Table 6, some of these hypotheses are significant, with p-values of less than 0.05 and 0.001, and the coefficient values are higher, indicating that the latent variable had a greater impact on behavioural intention. The results showed strong positive relationships between behaviour intention and several factors, including PE, FC, PV, EE, HM, HB, AIL and BI, which supported hypotheses H2, H3, H4, H5, H7, H9 and H10 with p values of less than 0.05 and 0.001. There is also a significant positive correlation between behaviour intention and UB, with a p-value of less than 0.001, which supports hypothesis H8. On the other hand, PE, TR and SI did not have a significant impact on behaviour intention, with p values greater than 0.05, so hypotheses H1, H6 and H8 were not supported. Overall, the results provide valuable insights into the relationships between various factors and behavioural intention and can inform future research in this area.

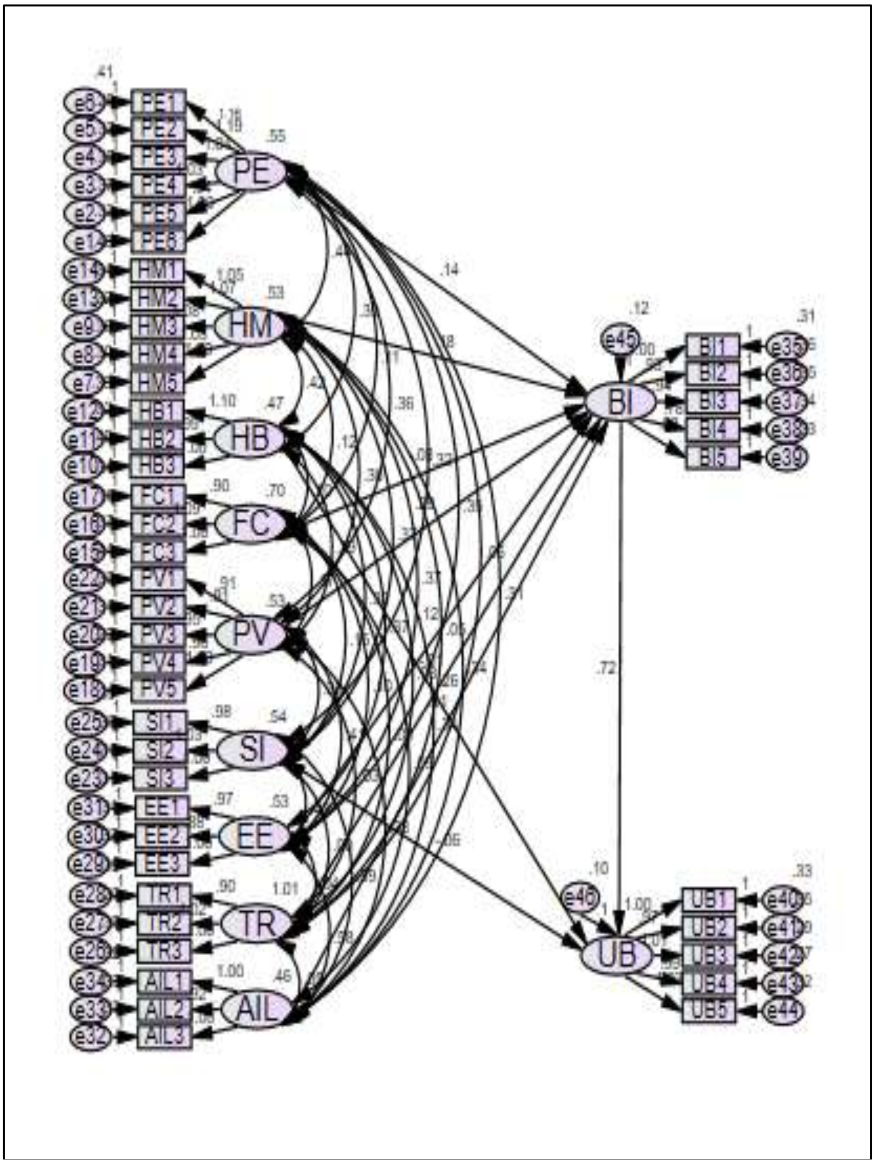

Figure 3: Structural Equation Model (SEM) generated using AMOS, illustrating the relationships among latent constructs [Performance Expectancy(PE), Hedonic Motivation(HM), Habit(HB), Facilitating Conditions(FC), Price Value(PV), Social Influence(SI), Effort Expectancy(EE), Trust (TR), AI Literacy (AIL)] and their influence on Behavioural Intention (BI) and Use Behaviour (UB).

Table 6: Hypothesis Testing Results

	Regression path		**SRW**	**p**
H1: Rejected	BI ← PE	Effect of PE on BI	0.135	0.042
H2: Supported	BI ←HM	Effect of HM on BI	0.178	0.019
H3: Supported	UB ← HB	Effect of HB on UB	0.249	0.001
H4: Supported	BI ← FC	Effect of FC on BI	-0.087	0.012
H5: Supported	BI ← PV	Effect of PV on BI	0.281	0.001
H6: Rejected	UB ← SI	Effect of SI on UB	-0.066	0.248
H7: Supported	BI ← EE	Effect of EE on BI	0.119	0.012
H8: Rejected	BI ← TR	Effect of TR on BI	-0.013	0.700
H9: Supported	BI← AIL	Effect of AIL on BI	0.288	0.001
H10:Supported	UB ← BI	Effect of BI on UB	0.743	0.001

Table 7: Structural Path Analysis

Regression path	**Questions**	**SRW**	**CR**	**AVE**	**SMC**
PE1 ← PE	AI tools help me complete my learning tasks more quickly.	0.802	0.91	0.64	0.643
PE2 ← PE	AI tools improve the quality of the assignments and learning outcomes	0.858			0.737

PE3 ← PE	AI tools make it easier to understand complex topics efficiently.	0.806			0.650
PE4 ← PE	AI tools significantly enhance my productivity in my studies.	0.787			0.619
PE5 ← PE	AI tools are useful in improving overall academic performance.	0.755			0.570
PE6 ← PE	AI tools assist me in making my academic studies and research more effective.	0.790			0.624
HM1 ← HM	I enjoy using AI tools during my learning activities	0.771	0.90	0.64	0.594
HM2 ← HM	Using AI makes my learning experience more interesting and engaging.	0.814			0.663
HM3 ← HM	I feel motivated to learn more when AI tools are involved	0.812			0.659
HM4 ← HM	AI tools make learning more fun, which helps me stay focused.	0.771			0.594
HM5 ← HM	The enjoyable experience of using AI improves my overall learning outcomes.	0.801			0.642
HB1 ← HB	I habitually use AI tools to support my studies and assignments	0.782	0.79	0.55	0.611
HB2 ← HB	AI technologies are a natural element of how I learn new academic subjects.	0.753			0.567
HB3 ← HB	I depend on AI tools whenever I face difficulty in understanding topics	0.689			0.475
FC1 ← FC	The institution's administrative AI tools are easily accessible for my academic needs.	0.792	0.89	0.73	0.627
FC2 ← FC	The institution offers adequate technical assistance when I face difficulties with AI-based administrative platforms.	0.938			0.880
FC3 ← FC	Training or orientation is available to help me understand and use AI in administrative tasks efficiently	0.809			0.655
PV1 ← PV	Using AI for my studies is worth the time it takes to learn it.	0.709	0.88	0.59	0.502
PV2 ← PV	AI gives me more learning benefits than the effort or money I spend on it.	0.771			0.595
PV3 ← PV	The advantages I get from AI in learning are worth the training and resources required.	0.777			0.603
PV4 ← PV	AI helps me save enough time and effort in my studies to make it worth using.	0.791			0.625
PV5 ← PV	Overall, AI is helpful for my education at a reasonable cost.	0.795			0.632
SI1 ← SI	Recommendations from friends or peers influence my decision to use AI tools.	0.773	0.78	0.54	0.597
SI2 ← SI	I use AI tools because many of my classmates also use them	0.766			0.587
SI3← SI	My teachers expect me to use AI in my studies.	0.649			0.412
EE1 ← EE	Interacting with AI tools requires minimal mental effort while completing my coursework.	0.784	0.82	0.60	0.615
EE2 ← EE	It is easy for me to become skilled in using AI tools for learning.	0.755			0.569
EE3 ← EE	I understand how to use AI tools for my studies without needing extensive help.	0.789			0.623
TR1← TR	AI tools used in education are more trustworthy when recommended by my institution.	0.845	0.91	0.77	0.713

TR2 ← TR	Even without supervision, I would trust AI tools to provide accurate content for my academic tasks.	0.915			0.838
TR3 ← TR	I believe AI tools are dependable for supporting my academic learning and assignments.	0.861			0.742
AIL1 ← AIL	I have a basic understanding of how AI tools work in educational settings.	0.764	0.80	0.57	0.584
AIL2 ← AIL	I can critically evaluate whether the output generated by AI tools is appropriate for my assignments.	0.733			0.537
AIL3 ← AIL	I understand the ethical considerations involved in using AI tools for academic learning.	0.764			0.583
BI1 ← BI	I intend to continue using AI tools regularly for my learning activities.	0.809			0.654
BI2 ← BI	I plan to use AI tools more frequently to support my studies in the future.	0.760			0.577
BI3 ← BI	I use AI tools to complete assignments and academic tasks.	0.773	0.86	0.55	0.598
BI4 ← BI	I expect to use AI tools whenever they are available for learning purposes.	0.695			0.483
BI5 ← BI	I would recommend using AI tools for academic learning to other students.	0.730			0.533
UB1 ← UB	I use AI tools frequently to complete my academic assignments.	0.769			0.591
UB2 ← UB	I regularly use AI tools to understand difficult or complex topics.	0.768			0.590
UB3 ← UB	AI tools are part of my day-to-day learning activities.	0.816	0.90	0.65	0.666
UB4 ← UB	I actively use AI tools during exam preparation or project work.	0.812			0.659
UB5 ← UB	Overall, I consistently utilize AI tools throughout my academic learning process.	0.788			0.622

5. Discussion

The proposed study contributes to our understanding of the application of artificial intelligence in higher education, particularly in Tamil Nadu, India. Students' ambition to use AI and their actual age are examined in relation to a number of aspects, including performance, ease of use, and available support. To examine the relationships between these variables and how they affect student behaviour, the study employed a unique approach. It is fascinating because it provides real-world examples from a rapidly evolving region of the world. It also helps explain why students do or do not use AI. All things considered; this study contributes to our understanding of what motivates students to use AI. It turns out that students' desire to adopt AI technology is significantly influenced by how simple it is to understand and use. They are more inclined to try it if it is easy. Who wants to spend a lot of time learning how to use anything? This makes sense. Additionally, prior research has demonstrated that individuals are more likely to adopt technology when it is simple to use. For instance, researchers such as Huang and Rudhumbu have found that a person's decision to adopt technology can be greatly influenced by its intuitiveness. Therefore, it is clear that the secret to winning over students to AI technology is to make it easy to use.

Behavioural intention was significantly predicted by Facilitating Conditions (H4), suggesting that acceptance levels are influenced by institutional support, technology infrastructure, and resource availability. This supports Tarhini et al (2014) and emphasizes how important it is to improve institutional preparedness for AI-driven change. Behavioural intention was significantly impacted by Price Value (H5) and Hedonic Motivation (H2). Students observe that utilizing AI technologies is both enjoyable and economical (Venkatesh et al., 2012; M. Raza, 2024). Technology that is both useful and entertaining promotes sustained engagement.
Habit (H3) had a substantial impact on usage behaviour, suggesting that automatic engagement habits are fostered by the consistent use of AI tools in routine academic procedures. This result highlights the regular use of technology in educational settings and is consistent with research by Grassini et al. (2024) and Singh et al. (2025). Students who have a better grasp of AI ideas, functionalities, and constraints are more willing

to use AI technologies for academic reasons, according to AI Literacy (H9), which significantly influenced behavioural intention. Students' acceptance and educational use of AI technologies are positively impacted by increased levels of AI literacy (Chiu, 2024; Z. Raza et al., 2025).

The basic tenet of TAM and UTAUT2that intention comes before usagewas supported by the strong prediction of actual usage behaviour by behavioural intention (H10). Students who showed interest in using AI for learning were more inclined to use it on a regular basis. Both Social Influence (H7) and Performance Expectancy (H1) had to be rejected. In contrast to previous studies (Ali et al., 2018; M. Kumar et al., 2025), performance expectancy had no discernible impact on intention. This suggests that students no longer view the use of AI as a differentiator, possibly as a result of its normalization in educational settings. Similarly, social influence had little impact, indicating that in this instance, personal experience and institutional support may be more significant than peer or instructor support.As generative AI technologies become more commonplace among students, there is less doubt and more acceptance, according to Grassini (2023). In AI-enabled learning contexts, future studies could examine whether trust acts as a moderating or mediating factor instead of a direct antecedent of behavioural intention.
Lastly, the results show that there are several primary reasons why students employ AI technologies. They are simple to use, to start. Additionally, organizations encourage their use, which is beneficial. They can even save money, and many people find them enjoyable to use. Using AI technologies simply becomes second nature over time. Certain elements that were once significant, like the opinions of people or the functionality of the instruments, are no longer as significant. People begin to choose the tools they want to utilize on their own as they get more at ease with technology.

5.1Theoretical Implementation

The UTAUT2 model was employed in this study as a useful framework for analyzing AI adoption practices in higher education. The need to expand conventional acceptance models by including user competency and knowledge-based dimensions is underscored by the substantial impact of AI literacy. The results imply that students' intention to employ AI tools is significantly influenced by their comprehension of AI technologies. Additionally, if AI technologies become more commonplace in educational settings, the non-significant effects of Performance Expectancy, Social Influence, and Trust suggest that traditional adoption factors may become less significant. Therefore, to better explain AI adoption behaviour in higher education, future theoretical models should incorporate emerging concepts such as AI literacy, ethical awareness, data privacy concerns, and responsible AI use.

5.2Practical Implementation

AI literacy development should be given top priority in educational institutions through training courses, workshops, curricular integration, and practical learning opportunities. Students' desire to use AI technologies for academic reasons can be greatly increased by developing their AI knowledge and abilities. Since trust was not proven to be a strong predictor of behavioural intention, educational institutions can concentrate more on making sure students know how to use AI tools and less on just marketing their dependability. Universities should keep making investments in supportive learning environments, sufficient technology infrastructure, and user-friendly AI technologies. Furthermore, including AI into regular academic tasks can support students' long-term adoption and reinforce habitual usage behaviours.

6Conclusion

Using the extended UTAUT2 model, the proposed study investigated the factors influencing students' acceptance and use of AI technology for learning in higher education. The results showed that AI adoption and usage behaviour were strongly influenced by Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, AI Literacy, and Behavioural Intention. AI literacy stood out among these variables as a significant predictor, indicating that students who have a better grasp of AI technologies are more inclined to accept and use AI tools in their academic endeavours. In contrast, there was no discernible correlation between behavioural intention and Performance Expectancy, Social Influence, or Trust.
The findings indicate that criteria about usability, accessibility, engagement, and user competency are becoming more important in driving AI adoption in higher education than performance expectations. The negligible impact of trust suggests that students may already believe AI technology to be sufficiently dependable, making trust a less important factor in adoption decisions. Rather, it seems that students are more focused on their comprehension and proficiency with AI technologies. Therefore, establishing AI literacy, bolstering technology infrastructure, encouraging responsible AI use, and integrating AI-driven systems into teaching, learning, research, and administrative procedures should be the main priorities for institutions looking to integrate AI in a sustainable manner. These programs can maximise the educational advantages of artificial intelligence in higher education and improve its long-term adoption.

6.1 Limitations and Future Recommendations

The study's focus on the Anna University South Zone in Madurai, Tamil Nadu, India, may limit the findings' applicability to other areas and educational settings. Self-reported measures were used to gather data at a specific point in time, which could be impacted by response bias. For deeper insights, future research should use longitudinal designs and incorporate behavioural data or qualitative techniques. Even yet, the model included AI Literacy and Trust. Future studies should examine the different aspects and moderating effects of AI literacy since it had a major impact on behavioural intention. Future research should look into Trust's possible mediating or moderating function in AI adoption, even if it was not proven to have a substantial direct effect. A more thorough knowledge of AI adoption in higher education would also be provided by comparing research across various AI technologies and learner categories.

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