Factors Affecting the Behavioural Intentions of the Users in Adopting Artificial Intelligence (AI) Tools in Higher Education

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ABSTRACT

In the global context, Artificial Intelligence (AI) is rapidly transforming higher education; however, its acceptance among students in developing nations, such as Sri Lanka, remains underexplored. With an emphasis on how specific attributes of AI influence the acceptance and use of AI, this study examines the behavioural intentions of Sri Lankan university students regarding the adoption of AI technologies, guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). The objectives of the research were to (1) identify the attributes of AI technologies that affect undergraduates' behavioural intention, (2) identify the impact of the attributes of AI technologies that affect undergraduates' behavioural intention, and (3) identify the impact of attitude on the relationship between those attributes and undergraduates' behavioural intention. A structured survey questionnaire was circulated among the undergraduate students, and IBM SPSS statistical software was used to analyse the collected data.

According to the findings, Performance Expectancy (PE) has a significant positive influence on behavioural intention, while Perceived Risk (PR), Effort Expectancy (EE), and Facilitating Conditions (FC) did not show significant effects. Furthermore, it was discovered that the association between behavioural intention and AI characteristics was partially mediated by attitude (ATT).

As the findings suggest, risk perceptions, ease of use, and institutional support appear to have a lesser impact on Sri Lankan undergraduates' readiness to adopt AI than their conviction that it may enhance their academic performance. This study extends the application of UTAUT in the context of Sri Lankan higher education, offering practical implications for universities and policymakers to highlight the academic benefits, foster positive student attitudes, and strategically integrate AI into educational practices.

Keywords: Artificial Intelligence, UTAUT, Higher Education, Technology Acceptance

INTRODUCTION

Artificial Intelligence (AI) is a groundbreaking field of computer science that has captivated the imagination of scientists, researchers, and the public for decades. It represents the culmination of human efforts to create technologies that can mimic human intelligence, perform tasks that typically require

human intelligence, and in some cases, even surpass human capabilities. The development of AI has had a profound impact on various aspects of our lives, including healthcare, transportation, entertainment, and education. Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems. Specific applications of AI include expert systems, natural language processing, speech recognition, and machine vision [4]. The demand for artificial intelligence (AI) in education is being driven by factors like the growing investments made in EdTech[1] and AI by both public and private sectors, as well as the

[1] Education and Technology

growing popularity of edutainment[2]. Furthermore, the global need for AI in education is being fuelled by technological advancements. The COVID-19 pandemic had a catastrophic impact on industries worldwide. Nonetheless, during the pandemic, the market saw a significant increase in demand for cutting-edge AI-based educational solutions [3].

In the Sri Lankan context, while universities have not yet widely incorporated AI technologies into their teaching approaches, undergraduates are actively embracing various AI technologies, including ChatGPT, Gemini, and Quill Bot, to enhance their effectiveness in completing assignments and projects [21].

Despite the increasing adoption of AI among university students, there is a notable lack of studies that specifically examine the dynamics of AI acceptance and usage within the Sri Lankan context. Moreover, numerous studies conducted on this subject have demonstrated the Technology Acceptance Model (TAM) as a suitable framework for understanding the adoption of preceding technologies. Other research in the user acceptance literature has proposed a variety of models that have been comprehensively examined and compared, yielding a unified model known as the Unified Theory of Acceptance and Use of Technology (UTAUT).

In brief, this study emphasises identifying the factors influencing the adoption of AI technologies in higher education using the UTAUT model. Accordingly, the following research questions have been formulated.

RQ1: What attributes of AI technologies affect undergraduates' behavioural intention in Sri Lanka?

RQ2: How do those attributes of AI technologies affect undergraduates' behavioural intentions?

RQ3: What is the impact of attitude on the relationship between those attributes and undergraduates' behavioural intention?

To address the research questions, this study is organised into six main sections. The Literature Review includes relevant studies and theoretical constructs related to AI adoption and UTAUT. The Methodology outlines the research design, data collection, and analysis methods. The Findings present the results of hypothesis testing, while the Discussion interprets these outcomes in relation to existing literature and the Sri Lankan higher education context. The Implications highlight both theoretical contributions and practical recommendations for universities and policymakers, and the References section lists all sources cited in the study.

LITERATURE REVIEW

Unified Theory of Acceptance and Use of Technology (UTAUT)

One of the first models to help understand people's acceptance of specific technologies is the Technology Acceptance Model (TAM). It was introduced in the field of information systems to predict better employees' ability to adopt computer-based technology in an organisational context, often described as predicting and explaining why a technology is more likely to be accepted or not [7]. For this reason, the model comprises fundamental determinants. Primarily relevant ones are perceived usefulness, "the degree to which a person believes that using a particular system would enhance his or her job performance," and perceived ease of use, "The degree to which a person believes that using IT will be free of effort" ([6], [7]).

Other researchers in the development of technology adoption agree with the TAM being an appropriate and well-established model to predict behavioural intention to use certain computer-based technologies [17]. However, it has been amended and developed throughout the years. The model was extended by adding social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use), resulting in the TAM 2 [15]. Later, the TAM 3 model was introduced to integrate a collection of pre- and post-implementation interventions that affect the determinants of technology adoption [15]. Other research in the user acceptance literature has brought up a variety of different models. Eight prominent models (Theory of Reasoned Action (TRA), TAM, motivational model, Theory of Planned Behaviour (TPB), combined TAM and TPB, model of PC utilisation, innovation

[2] Education with the goal of making learning enjoyable.

diffusion theory, social cognitive theory) have been comprehensively examined and compared, yielding in a unified model which is called Unified Theory of Acceptance and Use of Technology (UTAUT). The dimensions of UTAUT are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Perceived Risk (PR):

Perceived risk can significantly impact users' behavioural intentions and actual use of technology [15]. The higher the perceived risk, the less likely individuals are to adopt the technology, as they may fear errors, misuse of data, or lack of reliability [10].

Performance Expectancy (PE):

Performance expectancy refers to "the degree to which an individual believes that using the system will help him or her at performance" [15]. It is conceptually similar to perceived usefulness (from the Technology Acceptance Model, or TAM), relative advantage (from the Diffusion of Innovations Theory, or DOI and Innovation-Diffusion Theory, or IDT), and outcome expectations (from the Social Cognitive Theory, or SCT) [8]. Performance Expectancy was the most powerful determinant when forecasting behavioural intentions [18]. Additionally, they claimed that it is in proximity to utilities [9]. Customers are more willing to adopt a system if they believe it will save time and effort ([8], [13], [14]).

Effort Expectancy (EE):

Effort expectancy is "the extent of ease connected with the use of a system" [15]. The likelihood that a person will adopt a new system is not just determined by how highly that system is valued, but also by how easy it is to use [2]. According to some researchers, effort expectancy was a critical component in numerous studies on the diffusion of technology and innovation [10]. As Performance Expectancy, Effort Expectancy can be found alongside two more fundamental columns within the UTAUT, which predict the indicators that influence the behavioural motives for handling and needing technology [18]. They state that consumers take time and effort into consideration when forming a view of the overall effort for accepting and using a technology. This means that before deciding to buy or use a technology, consumers take the time to evaluate the effort required to receive and use it. Based on that evaluation, their likelihood to adopt the technology either increases or decreases. This would mean that two factors play a role within this: How high they evaluate the effort and whether they judge it to be aligned with the benefits they would gain from accepting and using such a technology.

Facilitating Conditions (FC):

"The degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" is referred to as facilitating conditions [15]. They regulate both behavioural intention and the usage of technology. This means that facilitating conditions reveal something about what consumers or potential future users need to adopt a technology, what factors or resources must be provided, or even what help they require to use or consider using a new technology properly.

Attitudes (ATT)

People express their feelings to carry out a target behaviour, whether it be positive or negative. This covers the sense of attitude [1]. The Technology Acceptance Model (TAM) states that a person's attitude towards using a system determines their behavioural intention [7]. Previous research indicates that behavioural Intention is influenced by attitude [5]. As found in other studies, attitude acts as a powerful mediating variable in interpreting behavioural intention.

Behavioural Intention (BI)

The term "behavioural intention" (BI) refers to the process of evaluating each person's contextual intention to carry out a particular behaviour [1]. The behavioural intention is a strong predictor of performing the actual activities in which that intention is expressed [22].

METHODOLOGY

As the study relies on hypotheses to determine the relationships between the independent variables and the dependent variable, it employed a deductive approach with a cross-sectional design. The population of this study consists of undergraduates from the University of Sri Jayewardenepura, who were selected using the convenience sampling method. An online questionnaire consisting of 23 statements was circulated among the undergraduates. The seven-point Likert scale, ranging from 1: "Strongly Disagree" to 7: "Strongly Agree", was used to measure the constructs. A total of 163 responses were collected from the respondents, and 3 responses were excluded as they were not completed correctly. The number of responses considered for analysis is 160. The processing of this sample was performed using IBM SPSS statistical software. The data analysis was conducted in two phases. The first phase consisted of testing the reliability and validity of the constructs. The second phase of data processing involved hypothesis testing using multiple linear regression, while the mediating impact was assessed using the Sobel test.

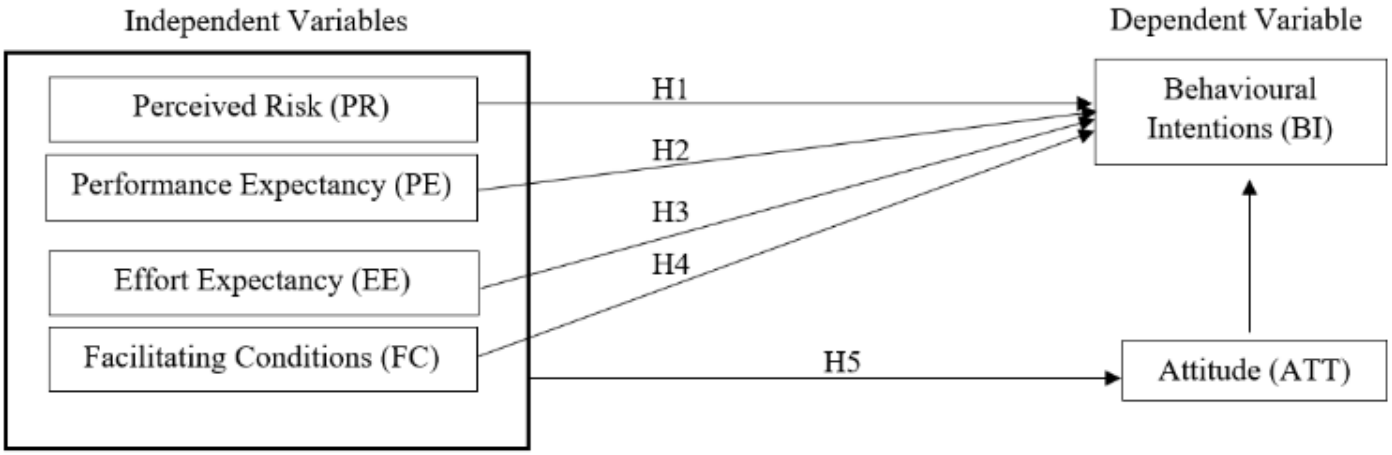

Fig. 1 Conceptual framework

H1: Perceived Risk (PR) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.

H2: Performance Expectancy (PE) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.

H3: Effort Expectancy (EE) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.

H4: Facilitating Conditions (FC) have an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.

H5: Attitudes (ATT) of individuals have a mediating impact on the relationship between the attributes and the behavioural intention (BI) of the users in adopting AI in higher education.

FINDINGS

Kaiser-Meyer-Olkin (KMO), Average Variance Extracted (AVE) and Cronbach's Alpha were used to measure the validity and reliability of the data. All the variables have high reliability, with Cronbach's Alpha values ranging from 0.731 to 0.903. All KMO and AVE values are higher than 0.5, indicating better sampling adequacy for factor analysis.

After confirming the reliability and validity of the dataset, descriptive statistics were used to analyse the demographic profile of the respondents and their usage patterns of AI tools. The majority of respondents were male (56.9%) and in their fourth academic year (63.1%), with most belonging to the Faculty of Management Studies and Commerce (70%). A vast majority of students (98.1%) reported using AI tools for educational

purposes, with 43.1% using them 1–5 times per week, 23.8% using them 5–10 times per week, and 33.1% using them more than 10 times per week. ChatGPT is the most widely used tool (100%), followed by Grammarly and Quill Bot (83.1% each). Smaller proportions use Mendeley (13.8%), DALL-E (2.5%), and other AI tools, such as Perplexity and Bard AI (10%). These findings provide a clear overview of the sample characteristics and AI tool usage, forming the basis for further analysis.

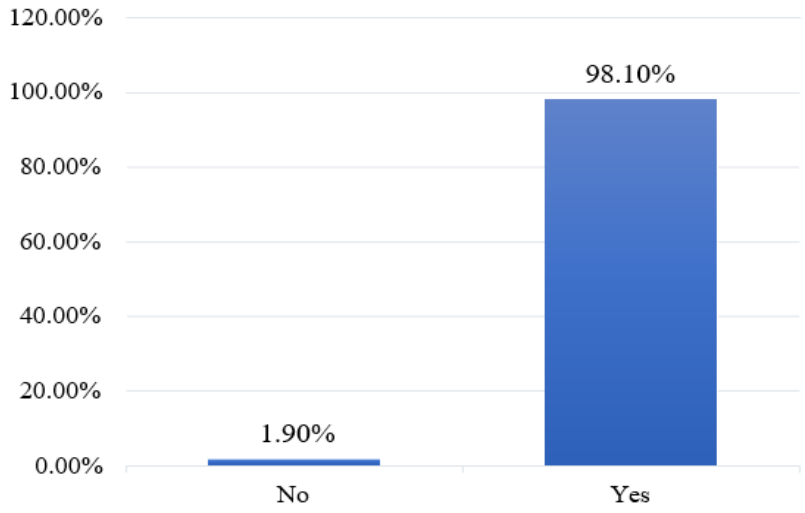

Fig. 2 Usage of AI tools

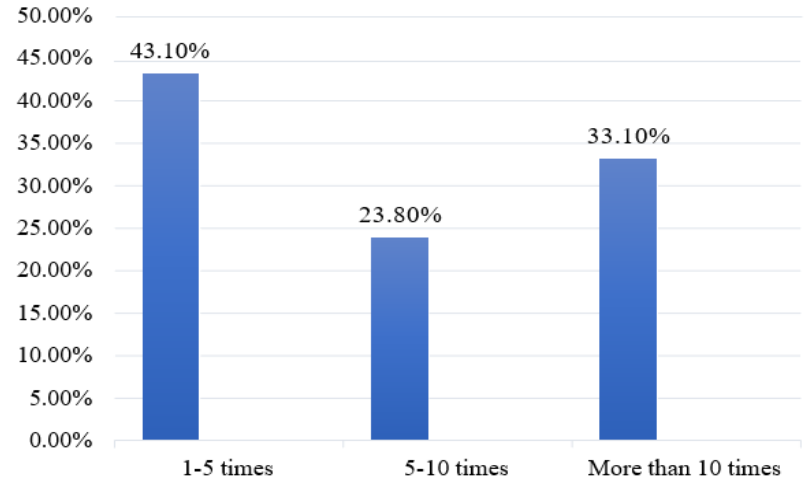

Fig. 3 Frequency of using AI tools (per week)

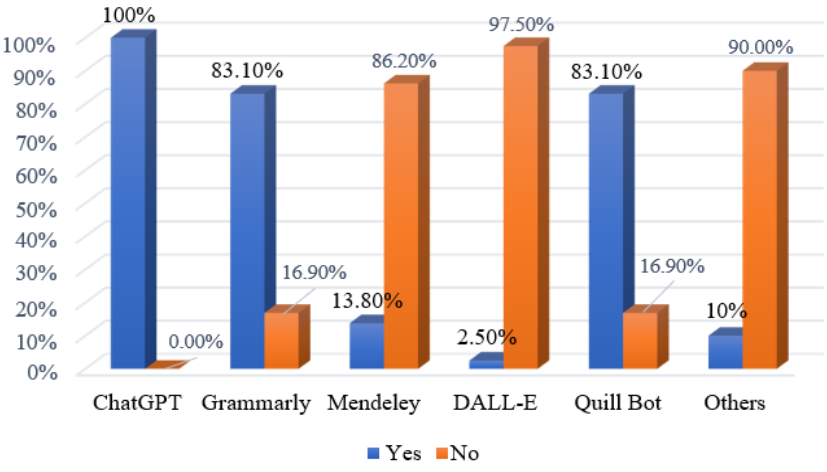

Fig. 4 Most used AI tools

The hypothesis testing results revealed mixed outcomes regarding the factors influencing students' behavioural intention (BI) to adopt AI tools in higher education. Perceived Risk (PR) showed a negative but insignificant effect on BI ($\beta = -0.068$, $p = 0.198$), leading to the rejection of H1. Performance Expectancy (PE) emerged as the strongest and significant positive predictor of BI ($\beta = 0.651$, $p = 0.000$), thus supporting H2. Effort Expectancy (EE) ($\beta = 0.060$, $p = 0.249$) and Facilitating Conditions (FC) ($\beta = 0.090$, $p = 0.066$) demonstrated positive but statistically insignificant effects on BI, resulting in the rejection of H3 and H4, respectively. Meanwhile, Attitudes (ATT) ($\beta = 0.616$, $p = 0.211$) revealed a positive but statistically insignificant direct effect; however, the results indicate partial mediation. Overall, these findings highlight that among the tested factors, only Performance Expectancy significantly predicts AI adoption intention, while Attitudes exert an indirect but meaningful influence through partial mediation.

Table I Results of the Hypotheses Testing

Hypothesis	Coefficient	P-value	Result
H1: Perceived Risk (PR) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.	-0.68	0.19	Rejected
H2: Performance Expectancy (PE) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.	0.65	0.00	Accepted
H3: Effort Expectancy (EE) has an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.	0.60	0.24	Rejected
H4: Facilitating Conditions (FC) have an impact on the behavioural Intention (BI) of the users in adopting AI in higher education.	0.90	0.66	Rejected
H5: Attitudes (ATT) have a mediating impact on the relationship between the attributes and the behavioural intention of the users in adopting AI in higher education.	-	0.21	Partially Mediated

DISCUSSION

The study investigated several hypotheses related to the adoption of AI in Higher Education, shedding light on key factors influencing users' behavioural intentions.

First, **Perceived Risk (PR)** was found to have no significant effect on BI **(H1)**. While prior research highlights the negative role of PR in shaping technology adoption ([8], [13], [14]), undergraduates in this study appeared to be less concerned about potential risks. This could be attributed to their increasing familiarity with AI tools, widespread exposure through social media and educational platforms, and a pragmatic tendency to prioritise task completion over risk considerations. Within the Sri Lankan higher education context, limited awareness of complex ethical or data privacy concerns may also explain the weaker role of PR in adoption decisions. This result contrasts with the existing literature and suggests that, in the context of higher education, users may perceive AI adoption as less risky than anticipated.

Second, **Performance Expectancy (PE)** demonstrated a significant positive influence on BI **(H2)**. This finding aligns with [15] and underscores that undergraduates are more likely to adopt AI when they perceive clear academic or performance-related benefits. This result highlights the utilitarian orientation of students, who often evaluate technologies based on their ability to enhance productivity, educational outcomes, or career competitiveness.

Third, **Effort Expectancy (EE)** did not significantly affect BI **(H3)**, diverging from the expectations of traditional models [7]. A plausible explanation is that current AI tools, particularly generative AI applications, are generally intuitive and require minimal technical expertise. For digitally literate undergraduates accustomed to user-friendly mobile and web-based platforms, ease of use may not be a decisive factor in adoption.

Fourth, **Facilitating Conditions (FC)** were also insignificant in shaping BI **(H4)**. Unlike in organisational settings where infrastructure plays a key role, Sri Lankan undergraduates typically access AI tools via personal mobile devices or laptops, bypassing the need for institutional infrastructure. This suggests that adoption decisions are driven more by individual readiness and personal devices than by institutional or technical support.

The result contrasts with earlier studies where FC influenced adoption ([8], [20]), indicating that in the student context, AI adoption is less reliant on formal institutional systems.

Finally, **Attitude (ATT)** was found to partially mediate the relationships between UTAUT attributes and BI **(H5)**. Although the statistical significance was limited, the positive association suggests that students' overall orientation towards AI can amplify their likelihood of adoption. This aligns with classic attitudinal models ([1], [7]), although the weaker effect indicates that behavioural intention is shaped more strongly by perceived usefulness than by affective evaluations.

Collectively, these findings highlight that among Sri Lankan undergraduates, the perceived benefits of AI (performance gains) outweigh concerns over risk, usability, or institutional support.

IMPLICATIONS FROM RESEARCH

This study extends the UTAUT framework by demonstrating its applicability in the Sri Lankan higher education sector. The results confirm that performance expectancy is the strongest predictor of AI adoption intentions, while traditional constructs such as effort expectancy and facilitating conditions were not significant. These findings suggest that in emerging markets where students are already digitally literate and mobile-first, conventional adoption barriers may be less relevant.

Future studies could address several limitations. A longitudinal design would enable tracking of how students' adoption intentions evolve as AI tools become more integrated into curricula and awareness of ethical and security issues increases. Mixed-method approaches combining surveys with qualitative interviews could provide richer insights into students' perceptions, uncovering the nuanced reasons behind their acceptance or rejection of AI. Comparative studies across countries or between different student groups (e.g., STEM vs. business students) may also reveal context-specific patterns.

The findings of this study also provide practical guidance for universities in fostering AI adoption among undergraduates. Institutions should prioritise highlighting the performance-related benefits of AI, as this factor has been found to influence students' behavioural intention significantly. This can be achieved by integrating AI-supported learning platforms into the curriculum, embedding AI applications within coursework, and offering hands-on training workshops that familiarise students with different tools. In addition, universities can run awareness campaigns that promote safe and responsible AI use, helping to address potential concerns about risks while also building student confidence in using these technologies.

From a policy perspective, government agencies play a crucial role in creating an environment that enables the adoption of AI in higher education. Policymakers can provide financial support through funding schemes and grants to encourage institutions to integrate AI-driven teaching tools. The development of clear national guidelines on the responsible and ethical use of AI in education would also help build trust and reduce hesitancy among stakeholders. Furthermore, incentivising universities to experiment with AI in teaching and learning can accelerate the digital transformation of higher education while ensuring that adoption aligns with broader national objectives.

For technology providers, the findings underscore the importance of designing AI tools that deliver substantial performance benefits, as this is the most decisive factor influencing students' intentions to adopt. Developers should focus on creating applications that are user-friendly, mobile-compatible, and adaptable to the academic requirements of undergraduates. Localisation is also a key feature, such as Sinhala and Tamil language compatibility, which would make AI solutions more accessible and relevant in the Sri Lankan higher education context. By tailoring tools to the specific needs of students, technology providers can enhance usability and increase adoption rates.

By collectively acting on these recommendations, universities, policymakers, and technology providers can create a supportive ecosystem that not only encourages AI adoption among undergraduates but also ensures that such adoption is both ethically sound and pedagogically meaningful, aligning with long-term policy goals.

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