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The Role of Behavioral Intention in AI Adoption and Student Success in Higher Education Institutions: A UTAUT2 Perspective

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ABSTRACT

This study examines the adoption of Artificial Intelligence (AI) tools in higher education, focusing on the factors influencing their acceptance through the UTAUT2 framework. AI technologies such as intelligent tutoring systems, virtual assistants, and chatbots are being implemented in universities to address challenges like high class sizes, limited academic resources, and the need for personalized academic support. The study investigates the impact of constructs including Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Social Influence (SI), Habit (HT), Price Value (PV), Perceived Enjoyment (PE), and Behavioral Intention (BI) on the adoption of AI tools by university students and their academic success. Data was collected from 324 students through web surveys and paper questionnaires, assessing their experiences with AI tools. Results indicate that Habit (HT), Price Value (PV), and Effort Expectancy (EE) positively affect students' Behavioral Intention (BI) to use AI tools, which in turn leads to enhanced academic performance and success. The study also emphasizes the role of institutional support, peer influence, and access to resources in fostering AI adoption. Additionally, it highlights the challenges faced by students in developing countries, such as limited digital access and infrastructure. The research provides valuable insights for policymakers and educators seeking to integrate AI tools into educational environments, particularly in developing regions. The study underscores the positive correlation between AI adoption and student success, offering recommendations to promote the effective use of AI technologies in higher education systems.

Introduction

Institutions of higher education (HEIs) are critical in fostering students' intellectual and professional lifelong development. These institutions must foster knowledge in their student's skills, and competencies vital to foster success in a dynamic and competitive global workforce. Nonetheless, HEIs encounter a host of challenges in fulfilling students' educational requirements, such as high class sizes, scarce academic resources, and inadequate personalized academic aid. All the good things cause the student to be disinterested, feel dissatisfied and have high dropout rates (Dahri,Al-Rahmi et al., 2024; Afaq et al., 2022) . This has initiated the wave of digitization of education and the spurt in digital learning environments have increased the demand to incorporate technological advancements like, Artificial Intelligence (AI) in education to develop, improve and make learning efficient and accessible (Al-Nory, 2012; Caratiquit & Caratiquit, 2023). To tackle these hurdles, educational institutions in different parts of the world are implementing AI tools to provide them with additional academic assistance. Intelligent tutoring, virtual assistants and chatbots are all AI-based systems providing personalized learning experiences, automated feedback and engagement of students (Dahri 2023). Such tools also allow for the creation of access for diverse and tech-savvy student populations. The demand for AI education has been increase speedily, and indeed, the practice of AI in education is most important mode impacting the learning of future (Bayne et al.,2020). So in this article the aim to apply the UTAUT2 framework that includes Performance Expectancy (PE), Price Value (PV), Habit (HT), Effort Expectancy (EE), Facilitating Conditions (FC), Social Influence (SI), perceived Enjoyment (PE), and Behavioral Intention (BI) and the beneficial outcome of Student Success (SS) (Tamilmaniet al.,2021) to analyze AI adoption process in higher education.

Performance Expectancy directly effects learners' intention to use the AI tool. It essentially means the level to which students think that these technologies will enhance academia performance of Students will more likely adopt AI tools in their studies, if they perceive these tools beneficial for studying (Almogren,et al.,2024). As a result, AI tools that equip students with individualized feedback, customized interventions, and tailored learning experiences can greatly enhance their learning results. Moreover, generative AI promotes engagement and collaboration, leading to topics for discussion and tasks to be solved (Pikhart, 2020). Personalized learning is another trend hand-in-glove with AI, as learning management systems designed to provide personal tutoring experiences through AI-powered systems placing the right resources in front of students based on their performance data become more prominent as well.

Facilitating Conditions relates to resources accessibility like a well-founded internet connection, technical support, and learning. These conditions affect students' capabilities to effectively use AI tools. Therefore, struggling with lack of infrastructure and having limited faculty support in an AI era may lead students to adopt such tools (Venkatesh et al., 2012). AI models are available for grading and provide blind evaluations, reduce educators' workload and improve grading accuracy for students in a classroom (Bin & Mandal, 2019; El Shazly, 2021). To practice these, universities have to ensure there is a sufficient amount of training and institutional support for the users of AI-based learning management systems.

Another crucial factor that influence students to use AI tools is Effort Expectancy. How easily users can interact with the AI system. When AI tools seem intuitive and user friendly to the students, it is likely that the students will use them during their learning procedure (Foroughi et al., 2023a). User-friendly AI platforms with seamless navigation enhance student engagement and satisfaction. How AI tools are branded and the way they are used will be a big part of how students embrace them, underlining the need to create simple to use and user friendly AI-powered learning experiences.

Peer and instructor recommendations take part a major character in the technology adoption for students (Aljaafreh, 2021). Similarly, when students see other students taking advantage from AI tools or receive support from instructors, and AI tools as beneficial and use them in their studies (Venkatesh et al., 2012). To implement AI-assisted learning applications successfully, a supportive institutional structure is required (Vighio, Foroughi et al.,2024) . Using AI in courses Faculty members that actively promote AI-powered tools in their coursework encourage better student engagement and adoption.

Price Value, provides an analysis of the cost-benefit ratio for AI adoption in education, students are more retaliative for artificial intelligence tools where they got cost effectiveness and value (Moorthy et al., 2019). Habit signifies students' inclination towards the use of AI tools through repetitive use as being acquainted with the application leads to its long-term usage (Venkatesh et al., 2012). Perceived Enjoyment is the fun and pleasure that people get out of using AI tools; the more fun and engaging an experience is that involves AI, the more AI will be used (Venkatesh et al., 2012).

By giving students regular access to AI tools, incorporating them into their learning processes, and providing continual technical support, educational institutions can encourage AI adoption. Behavior Intention consists on Students motivation and willingness to use AI tools. Those with a positive intention to use AI tools have higher adoption rates, which result in better learning experiences and further improved academic performance(Azizi et al., 2020). With the increasing practice of AI-based platforms, students can be equipped enough to give their best, leading to better academic results.

While AI is increasingly adopted in higher education, limited extant research has studied which factors determine AI tool adoption, particularly in the context of developing nations. A considerable portion of the existing literature has focused on developed nations, where students often have greater access to technology and digital literacy resources (Foroughi et al., 2023). Unlike students in prosperous locations, students in developing countries like Pakistan grapple with digital access, infrastructure, and reluctance to integrate technology into standard learning frameworks. Very few empirical studies previously investigated how habits and social influence inbound during the readiness of the learners to practice AI tools in these cases. Filling this research gap is key to understanding how AI can be integrated into less developed educational systems.

Research Objectives

- Examine the impact of UTAUT2 constructs on the adoption of AI tools by university students.
- Determine the implications of AI tool usage on students' satisfaction and academic performance.
- Analyze the prospects and challenges of AI integration into the education systems of developing countries.

Research Questions

1. In what ways do UTAUT2 constructs influence AI tool utilization among students in higher educational institutions?
2. How does the incorporation of AI influence the academic performance and satisfaction levels of students?
3. What are the major challenges and possibilities of AI inclusion in the education systems of developing countries?

This study targets to examine the reasons behind the acceptance of AI by university students using the UTAUT2 model. This study hopes to examine specifically the impact on the BI of students to use AI tools in learning, of the PE, EE, FC, SI and HT concepts. Moreover, the present research will examine the effect of using AI devices on students' academic performance and overall satisfaction. Through its study of AI adoption in the wider context of HEI's, this research will elucidate which elements are most conducive to integrating AI into the learning experience, a fact that will be of great significance to policymakers, educators and technology professionals alike who are trying to impact the higher education landscape. Furthermore, this research will play a part to the existing literature by bringing evidence from a developing country perspective, where contexts may be favorable (i.e. less automation) or unfavorable (i.e. socio-political challenges) to AI innovation in education and where uptake of AI in education division is yet at an initial stage.

Literature review

The rise of the many faces of Artificial Intelligence (AI) across Higher education has brought plenty of buzz and talk about the transformative role of this technology on learning and teaching. Artificial Intelligence (AI) has played a remarkable part in the success of educational domain, here are a few of the examples of AI-driven tools which have greatly improved the engagement and academic performance of students such as the intelligent tutoring systems, (Su & Yang, 2023) automated feedback systems and personalized learning platforms (Talan & Kalınkara, 2023;) AI technologies that are rapidly developing have provided universities with new methods to provide effective knowledge and can solve challenges such as numerous pupils in one course and a lack of academic staff . According to AI research, AI-driven educational technologies enable students to access information in dynamic ways, improve their cognitive processing, and create collaborative learning environments. This transformative technology in the field of higher education, we know from empirical studies with students that they can engage repeatedly via a learning experience as peers on robust discussion topics, role playing situations & complex problem solving tasks (Ahmad et al., 2023; Strzelecki & ElArabawy, 2024). Moreover, AI-based learning environments support the accomplishment of students by presenting suggestions for managing time and motivation regarding studying content (Michel-Villarreal et al., 2023). The use of AI in education, however, relies on various other factors including digital infrastructure, accessibility, and institutional readiness (Eager & Brunton, 2023).

Determinants of AI Adoption: The UTAUT2 Model Perspective and Theoretical Underpinning

Modeling these factors using (UTAUT2) might help to gain deeper understandings into AI adoption behavior in higher educational institutes. Originally, Venkatesh et al.'s UTAUT2 (Rudhumbu, 2022) which extends the original model UTAUT (2003) through adding three more constructs, (Perceived Enjoyment, Price Value, and Habit), which they call UTAUT2 (2012). Theory initial presents the notion of four constructs that affect whether an individual will intend to use technology or not; PE, EE, SI and FC (Yeou, 2016). UTAUT framework described user behavioral intention variance of 60% to 70%, while previous models explained 27% to 40% of variance (Yeou, 2016; Venkatesh et al., 2003).

Performance Expectancy (PE)

Students' attitude towards utilizing AI tools for learning purposes is greatly influenced by performance expectancy (PE). It entails the student belief about how AI technologies might improve their academic performance and learning outcomes (Dahri et al., 2024a). AI-based applications, including tutoring systems, automated assessments, and personalized learning platforms, have been shown to enhance student understanding, retention, and academic performance (Pikhart, 2020). If students notice that these are tools that can help them academically, their acceptance of these tools, even AI, in their study rises (Tang et al., 2025).

H1: There is a positive relationship between Performance expectancy and students' Behavior intention.

Effort Expectancy (EE)

EE is the perceived ease of use of AI tools for educators. Research has demonstrated that user friendly designs, intuitive interfaces, easier navigation of AI platforms are key levers to boost student engagement and encourage the adoption of technology (Foroughi et al., 2023). AI-powered learning management systems that emphasize accessibility and usability can lower the cognitive load on students and broaden the participating student body. But if students struggle to use AI apps the uptake may be minimal (Corrin et al., 2023). This means that the way that AI tools is easily available to students directly affected intention of adopting education expectation according to them. Thus, we can formulate our first hypothesis as follows:

H2: There is a positive relationship between Effort Expectancy and students' Behavior Intention.

Social Influence (SI)

SI is another important factor affecting students' attitudes towards AI adoption. Such recommendations from fellow students, encouragement from faculty members, and endorsement from their institutions are critical for students' use of AI-powered educational tools (Zawacki-Richter et al., 2019). When educators meaningfully incorporate an AI application into their target audience, students view AI as integral to their learning journey (Wang et al., 2024). Students tend to have higher intent to adopt an AI tool when they focus on what their peers gain from the tool (Li, 2023).

H3. There is a positive relationship between Social influences and students' Behavior Intention.

Facilitating Conditions (FC)

FC which includes the infrastructure needed to adopt AI, including stable Internet facilities, technical support, and institutional resources (Bile Hassan et al., 2022). Wherever digital infrastructure and trainings were well-developed so that students can benefit from AI tools in education (Al-Fraihat et al., 2020). Moreover, students are more likely to adopt learning solutions driven by AI if they have access to adequate resources and institutional aid.

H4. There is a positive relationship between Facilitating Conditions and students' Behavior Intention.

Perceived Enjoyment (PE)

PE is the enjoyment students obtain from using AI tools in the education. If students had a pleasurable experience while learning with AI, they seemed to be more willing to accept and use them continuously (Holdack et al., 2022; Pantano, 2014). Such engaging and interactive learning experiences will be powered by AI-based platforms that motivate and foster participation. It should also be noted that engaging experiences, can lead to increased uptake of learning technologies (Li, 2023). Existing studies have emphasized that PE can positively affect users' behavioral intention by enhancing their engagement with a task and also creating positive emotional attachment with technology (Xu & Thien, 2025).

H5. There is a positive relationship between Perceived Enjoyment and students' Behavior Intention.

Price Value (PV)

PV has a major impact on consumer behavioral intentions. It particularly indicates user perceptions about the usefulness and price of a technology in context to their intentions towards its use (Dwivedi et al., 2019; Venkatesh et al., 2012). Thus, when consumers perceive a technology to be cost-effective and providing good value for money, they are more likely to adopt and use it (Amrani & Najab, 2022). Tons of research shows that PV plays a great part in the acceptance of innovations like mobile learning (Azizi et al., 2020), e-learning (Mehta et al., 2019), and ChatGPT (Strzelecki et al., 2024). (Romero-Rodríguez et al., 2023) PV also plays a significant role on students' behavior in adopting such educational technologies as ChatGPT. Therefore in this research we consider PV to be a significant predictor of adoption intention as well as usage behavior of AI technologies for student success.

H6. There is a positive relationship among Price Value and students' Behavior Intention.

Habit

Habit is defined as "the extent to which individuals engage in behaviors automatically" (Casey & Wilson-Evered, 2012 p. 2035). According to (Moorthy et al., 2019) Habit is defined as the level of automatic use of a system by an individual, without any conscious effort at all. This means despite the fact that habit refers to behaviors that have become routine or nearly automatic. How automatically students use AI tools when learning. An habitual behavior of AI use increases the likelihood of students to continue to use AI-powered learning environments (Aljaafreh, 2021).

H7. There is a positive relationship among Habit and students' Behavior Intention.

Behavioral Intention and Student Success

BI is very important for students to succeed. Behavioral intentions describe the possibility that an individual will enact a specific behavior (Azizi et al., 2020). According to a research by Al-Maroof et al. (2021), the integration of AI tools deepened the students' learning experience, and students with AI tools performed better in their academic pursuits and were more engaged. Students are more likely to gain personalized learning, immersive content, and AI-based academic assistance systems when they form such strong behavioral intentions towards adopting AI technologies (Shaya et al., 2023).

H8. There is a positive relationship among Behavior Intention and student success.

Behavioral Intention and Artificial Intelligence

Behavioral Intentions is heavily influenced student to use of AI tools. When students form positive intentions toward using AI tools, they are more likely to involve with AI-based educational technologies (Ghimire et al., 2024). According to (Abbad, 2021), students with a strong BI towards AI are more persuaded to embrace AI tools for personalized learning, AI-assisted academic support, and immersive learning experiences. This engagement empowers them to enhance their learning more effectively; after all, AI can personalize the experience to match their learning style, give them immediate feedback when needed, and customize the content based on their brain bandwidth (El-Sisi, 2025).

H9: The relationship among Behavior intention and Artificial Intelligence is positive.

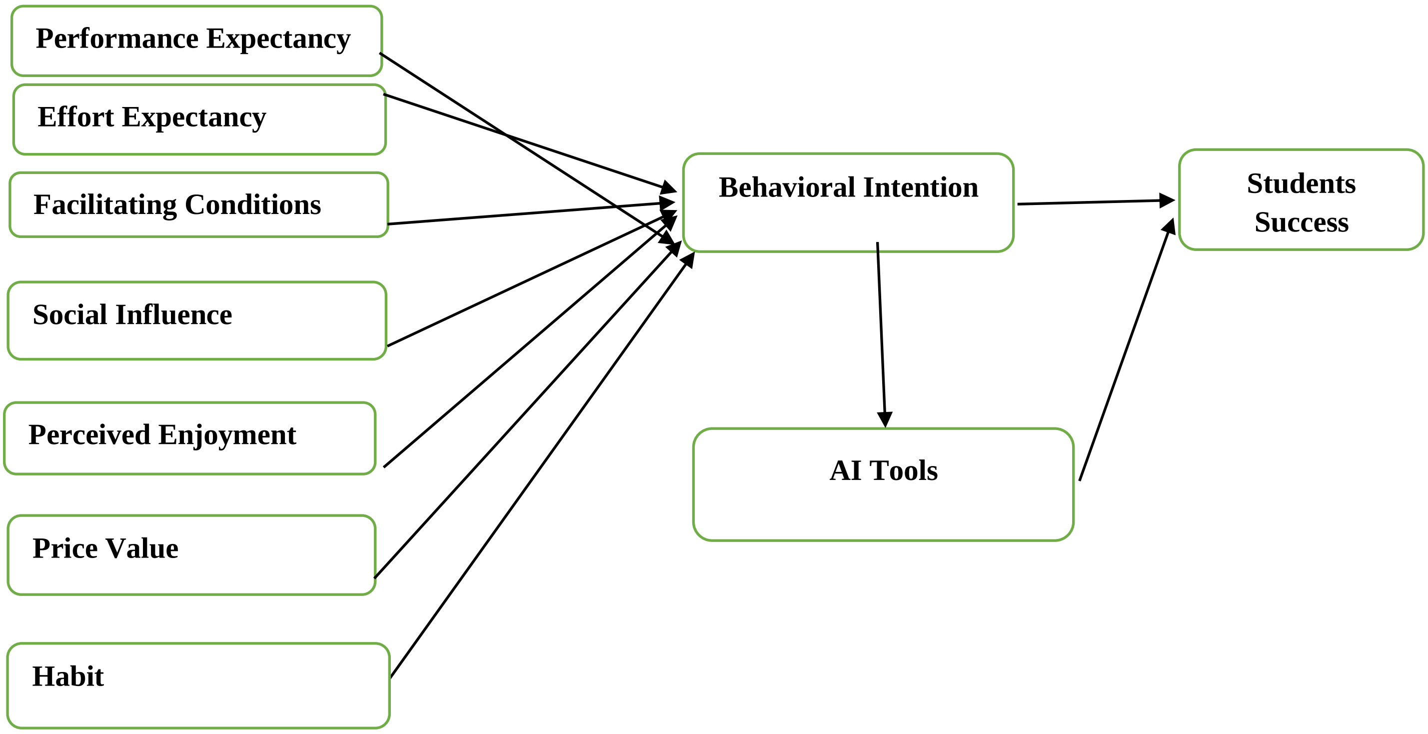
Artificial Intelligence and Student Success

Artificial Intelligence (AI) is one of the most effective way to help students succeed with self-learning with real-time feedback and obtaining insights about their performance based on the data.

The study by (Saha et al., 2025) underlines how AI tools are deepening students' learning experiences, which helps students understand complex concepts with ease. From intelligent tutoring systems and automated grading systems to adaptive learning platforms, AI systems help students study by offering personalized support to overcome learning barriers. Use of AI Tools In this regard, students who are using AI tools are generally more involved with their studies, which translates into strong performance and greater success (Njoku & Wey-Amaewhule, 2025).

H10. There is a positive relationship among the Behavior Intention and Student Success.

Theoretical Model using UTAUT2



Research methodology

Sample Selection and Data Collection

The data was collected from students enrolled in coursework programs at Higher Education Institutions (HIEs) in Bahauddin Zakariya University, Institute of Southern Punjab, Emerson University, NFC Institute of Engineering and Technology, and Air University Multan. Participants were selected based on their awareness and usage of different AI tools for academic goals. The sample comprised undergraduate and postgraduate students who actively used AI tools during their studies, aligning with the study's objective of exploring AI as a potential academic support.

Data collection took place in the middle of November 1 and December 30, 2024, through both online and offline methods. A web survey link was distributed via students' class WhatsApp groups, while paper questionnaires were administered in classrooms by co-authors. The questionnaire used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) to assess AI tool usage, academic performance, and demographic variables. A cover letter accompanying the survey explained voluntary participation and ensured respondent anonymity.

Out of 400 questionnaires distributed, 355 responses were received (response rate: 88.75%). Please note that 31 responses were excluded for lack of variability, leaving us with 324 valid responses. No major outliers were found on univariate outlier analysis. Non-response error was minimized by assuring respondents of anonymity and confidentiality, a short and simple survey.

Common Method Bias (CMB) was evaluated using, Harman's single-factor test and full collinearity test and it showed no concern of CMB (Harman, 1976; Kock & Lynn, 2012; Podsakoff et al., 2003). Data was readied for analysis using SEM based on the suggestions of (Hair et al., 2012) to preserve the integrity of statistics.

Measurement Instruments

The items adapted from the UTAUT2 framework and also those other validated sources were systematically structured into a questionnaire to solicit information that is pertinent to this research. This survey contained two sections the first section collected basic demographic information such as gender, age, education level, and usage of AI tools by the students. In the second section of the form, participants were questioned regarding key constructs based on the UTAUT2 framework, namely PE, EE, FC, SI, and PV together with BI. To be consistent with the present study context, these items were somewhat altered following (Cabrera-Sánchez et al., 2021). Fifty-three items were included as part of the tool, selected to ensure that the tool incorporated the key intended constructs.

Piloting the Questionnaire

Here, a pilot study was performed with 60 university students to evaluate the dependability of the instrument before proceeding with full-scale analysis. Cronbach's alpha was reported as a measure of internal consistency, with which a value of 0.7 or higher was used as a cut-off for acceptable reliability (Hair et al.). (2006, 2017). The results indicated that all measurement constructs met this standard, so the questionnaire was suitable for SEM (structural equation modelling) analysis.

Data Analysis

Data were analysis using the SPSS (Statistical Package for Social Science) and SmartPLS 4.0 for structural modelling. A two-stage approach was used (Foroughi et al., 2023; Hair et al., 2012, 2019). In the first phase, we evaluated construct dependability, convergent validity, and discriminant validity. Subsequently, the second stage was performed to assess the structural framework, investigating for both direct and indirect impact of the constructs.

Results

Preliminary Analysis

This research focuses on students enrolled in Higher Education Commission (HEC)-sponsored higher education institutions. A total of 400 questionnaires were distributed to gather the required data. Out of these, 324 valid responses were received through Google Forms, reflecting the answer rate of 81%. According to (Nulty, 2008), a response rate between 32% and 75% is generally acceptable for academic surveys. Hence, this response rate demonstrates both effective survey design and strong participant engagement with the topic.

A preliminary analysis was conducted to review the demographic profile of the participants, which included variables such as gender, age, occupation, education level, income, marital status, and nationality. A summary of the respondent characteristics is provided in Table 1, highlighting the diversity of the sample.

Table No. 1

Characteristics.	No	%
Gender of respondents:		
Male respondents.	221	68.2%
Female respondents.	103	31.8%
Age of respondents.		
15 - 20 Years.	104	32.1%
21 - 25 Years.	212	65.4%
26 - 30 Years.	6	1.9%
31 - 35 Years.	2	6%
36 - 45 Years.	0	0%
Education:		
Bachelor	275	84.9%
Master	41	12.7%
M.Phil.	07	2.2%
Ph.D.	1	3%

This data shows that the majority of respondents were male (68.2%), with female respondents making up 31.8% of the sample. Regarding age, 65.4% of participants were between 21 and 25 years old, followed by 32.1% in the 15–20 age bracket. A smaller number belonged to the 26–30 (1.9%) and 31–35 (0.6%) age groups, while no responses were recorded from the 36–45 age category, indicating a predominantly younger student population.

In terms of educational qualifications, most respondents (84.9%) were pursuing or had completed a bachelor's degree, reflecting the early academic or professional stage of the sample. 12.7% held a master's degree, and 2.2% were M.Phil. scholars, while only 0.3% had earned a Ph.D., suggesting limited representation from advanced research scholars.

This demographic profile confirms that the survey effectively captured a broad yet focused sample of young, educated individuals within HEC-supported institutions.

Internal Consistency Reliability

Cronbach's Alpha

Cronbach's alpha is a well-known measure of construct dependability or internal consistency within a research model. This measures the extent to which there is a similarity or correlation between items that are being used to calculate the same latent construct so that the scale you are using is reliable. According to Hair et al. Low reliability lies at alpha = 0 while high reliability is at alpha = 1. A higher Rosenthal value above 0.7 is often deemed acceptable for internal consistency. In the context of this study, the Cronbach's alpha was calculated to be 0.723, and thus internal reliability proved to be satisfactory and fulfilled the criterion. This is the value shows that the measurement items are consistent to represent constructs of research model (Kılıç, 2016).

Composite Reliability (CR)

Composite Reliability (CR) is another criteria that investigate the internal consistency of items under the same construct. This is especially important in Confirmatory Factor Analysis (CFA) for the examination of latent variable reliability (Hensley, 2009). CR is a combination of the item loadings, the variance between these loadings (how similar or different they are) and how sensitive they are to the construct. As per Hair et al. (2014), in general, a CR above 0.7 is good, while values around 0.6 can also be considered acceptable depending on the research set-up. Given the lower cut-off threshold of 0.5 for the reliability score (Hair et al., 2012; Hanafi & El Qannari, 2006), items reflecting below the cut-off threshold were removed to improve the validity and robustness of the measurement framework.

Convergent Validity

Essentially, convergent validity is concerned with whether a collection of indicators accurately captures the underlying theoretical phenomenon it aims to measure. Convergent validity is evaluated using the Average Variance Extracted (AVE), which should be greater than 0.5 [29]. AVE indicates the percentage of variance that the construct accounts for in relation to measurement error variance. For example, with reference to the recommended thresholds of AVE, an AVE value greater than 0.50 indicates an acceptable level of convergent validity because the items account for more than half of the variance of the latent construct (Hair et al., 2011, 2012, 2013, 2014; Henseler et al., 2009).

We evaluated the factor loadings for all items in this study before examining the measurement model. Items with lower loadings than an acceptable threshold (generally 0.6 or 0.7) were removed to increase the validity. The measurement framework already presented for the final one, with Cronbach's Alpha, Composite Reliability (CR) and AVE.

Measurement Model Analysis

Table 2:

Variable Name	Item Name	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Performance Expectancy	PE1	0.719700	0.604291528	0.76335562	0.501
	PE2	0.702435			
	PE3	0.736955			
	PE4	0.791265			
Effort Expectancy	EE1	0.788390	0.75436862	0.84276940	0.57655207
	EE2	0.796154			
	EE3	0.817525			
	EE4	0.811046			
Facilitating Conditions	FC1	0.709507	0.718012271	0.82524004	0.54236923
	FC2	0.716127			
	FC3	0.788904			
	FC4	0.765525			
Social Influence	SI1	0.756330	0.704292564	0.81571674	0.52794157
	SI2	0.784831			
	SI3	0.767684			
	SI4	0.742197			
Perceived Enjoyment	PE1	0.733035	0.626715327	0.78199929	0.48305242
	PE2	0.756033			
	PE3	0.792388			
	PE4	0.722042			
Price Value	PV1	0.777743	0.754967979	0.84459801	0.57688286

	PV2	0.787519			
	PV3	0.803796			
	PV4	0.753833			
Habit	HT1	0.723314	0.725379851	0.82926691	0.54851395
	HT2	0.730535			
	HT3	0.767888			
	HT4	0.739958			
Behavioral Intention	BI1	0.731694	0.732285091	0.83381815	0.55822717
	BI2	0.792332			
	BI3	0.740482			
	BI4	0.803139			
Student Success	SS1	0.732969	0.708807842	0.81950379	0.53205522
	SS2	0.775294			
	SS3	0.712326			
	SS4	0.704612			

CR= Composite Reliability, AVE= Average Variance Extracted

These are the resulting from the Measurement Model Analysis for AI tool adoption in Higher Education based on the UTAUT2 framework to ascribe on which point is a positive impact on students BI of using AI tools for Academic purpose.

Performance Expectancy (PE): The PE dimension explains that students who have a belief that AI tools will enhance their academic performance are more likely to adopt them. For PE, item loadings vary from 0.7197 for PE1 to 0.7913 for PE4, which are both satisfying factor loadings. Although this alpha value is α=0.6043 < 0.7, the Composite Correlation (rho_c), equals 0.7634, is acceptable, mild reliability. The Average Variance Extrated (AVE) value of 0.501 shows that the construct itself describes more than half of the variance in its items, hence adequate.

Effort Expectancy (EE), or perceived ease of use of AI tools by students, has very strong loadings across all items, ranging from 0.7884 to 0.8110 (EE1, EE4). With a Cronbach’s alpha of 0.7544, it exceeds a cut-off, showing good internal consistency, while a Composite Reliability of 0.8428 indicates a high construct reliability. An AVE of 0.5766 indicates that a considerable amount of the variance is accounted for by the construct, which is adequate.

Facilitating conditions (FC), that is, the essential tools and infrastructure for using the AI tools, report acceptable loadings between 0.7095 (FC1) and 0.7889 (FC3). With a Cronbach’s alpha score of 0.7180, there is reasonable internal consistency and the Composite Reliability of 0.8252 is provided strong results as well the value of AVE 0.5424 is sufficient, thus construct explains a certain share of the variance.

Social Influence (SI) emphasizes peer and faculty support for AI adoption. SI has loadings between 0.7563 (SI1) to 0.7848 (SI2) all of which are high. The obtained internal consistency (Cronbach’s alpha: 0.7043) is acceptable, and Composite Reliability (0.8157) indicates good reliability. A reasonable explanation of the items in the construct is compared to their relationships with other constructs, given an AVE of 0.5279.

For Perceived Enjoyment (PE) which is fun and enjoyment the students receive from using AI tools, the loadings range from 0.7330 for PE1 and6717 for PE3. While the majority of the items have high loadings, one item, PE4, has a loading (0.7220) that is comparatively lower. It ranges from 0.6267 < α < 0.7, indicating slight underperformance but trustworthiness to work on later. Similarly, the Composite Reliability is 0.7820 with the AVE at 0.4831 is slightly low, especially

PE4 showed lower loading with respect to the outer loading - which might deserve further attention to get better scale.

Price Value (PV) relates to the relative cost-benefit of having to use AI tools, i.e. all items evidenced strong loadings, with varied values ranging from 0.7777 for PV1 and 0.8038 for PV3. A Cronbach's alpha of 0.7550 is good, and a Composite Reliability of 0.8446 are very high, which indicates their good reliability. AVEs of 0.5769 indicates that the construct explains a reasonable amount of variance.

For habit (HT), which considers the extent to which AI tools are used regularly, we see good loadings ranging from 0.7233 for HT1 to 0.7679 for HT3. The constructed Cronbach's alpha is acceptable (0.7254) while Composite Reliability shows good internal consistency of constructs (0.8293). With AVE of 0.5485 showing satisfactory variance explanation for the construct.

Behavioral Intention (BI) capturing students' intent to use AI tools lies within the range of loadings from 0.7317 for BI1 to 0.8031 for BI4. The Composite Reliability of 0.8338 was strong and the Cronbach's alpha of 0.7323 was acceptable. A construct should be able to account for a reasonable amount of variance (AVE) to get a better picture, in the case of our results (0.5582).

The Student Success (SS) latent variable, reflecting the effect of using Academic AI tools on academic performance, had loadings ranging from 0.7046 (SS4) to 0.7753 (SS2). Both the Cronbach's alpha of 0.7088 and Composite Reliability of 0.8195 are good, indicating good internal reliability. AVE of 0.5321 shows that the construct captures more than half of the overall variance showing that the construct has good reliability.

The constructs are all reliable and valid, except the one concerning Perceived Enjoyment (PE), which has shown to have lower internal consistency and lower explained variance. In summary, this model offers some useful insights into the effect of Performance Expectancy, Effort Expectancy, and Facilitating Conditions on students' Behavioral Intention to use AI tools in higher education, eventually culminating to Student Success. Refinement of the Perceived Enjoyment construct can make the model more robust.

Table 3: R Square

Variable	R-square
Behavioral Intention	0.525
Artificial Intelligence	0.364
Student Success	0.405

The R-squared values describe the explanatory power in the model dependent-dimensional representation to the independent-dimensional representation. R^2 of 0.525 for Behavioral Intention (BI) shows that 52.5% variance is explained, which suggests that the factors of the model have a strong influence. The linear model for the adoption of Artificial Intelligence (AI) has a R^2 of 0.364, which means that 36.4% of the variance is explained — moderate, but be aware that other factors may also be at work. SS ($R^2 = 0.405$, $F(1, N) = 91.10$ p 1.96 and $p < 0.01$. The more rigorous criterion, the Fornell-Larcker criterion, examine only item loadings, and the more relaxed, the cross-loadings. Together these two methods verify that the constructs are distinct, valid constructs in the model and are reliable.

Structural model result

Direct Effects

Table 4:

Hypothesis	Relationships	Sample (O)	Mean (M)	STDEV	T-Stat	P Value
H1	PE -> BI	0.041	0.044	0.05	2.01	0.045
H2	EE -> BI	0.17	0.168	0.058	2.917	0.004
H3	FC -> BI	0.075	0.077	0.069	2.05	0.041
H4	SI -> BI	0.041	0.041	0.07	2.05	0.041
H5	PE -> BI	0.125	0.13	0.055	2.271	0.023
H6	PV -> BI	0.218	0.215	0.064	3.388	0.001
H7	HT -> BI	0.237	0.234	0.061	3.871	0.000
H8	BI -> SS	0.579	0.581	0.044	13.019	0.000
H9	BI -> AI	0.603	0.606	0.033	18.339	0.000
H10	AI -> SS	0.333	0.333	0.06	5.546	0.000

Structural Model Results: From the above results, it can be seen that multiple factors have the substantial impact on Behavioral Intention (BI) of using AI tools in education. Effort Expectancy (EE) has a coefficient of 0.17, indicating a moderate impact on BI, suggesting that perceived ease of use of AI tools is a positive driver of students' intentions to use them. Assessment of the coefficients also indicates that Price Value (PV) has a substantial impact on BI (0.218), demonstrating that students are more inclined to use AI tools when they find them affordable. The strongest effect on BI (coefficient = 0.237) is demonstrated by Habit (HT), meaning the students who organized the habit of using AI tools are more likely to do so.) Similarly, Facilitating Conditions (FC) and Social Influence (SI) both have positive effects on BI albeit with lower coefficients of 0.075 and 0.041 respectively. The availability of resources, along with peer or instructor support, contributes to students' intention to deploy AI tools.

BI is a significant antecedent in predicting AI adoption and SS. There is a strong positive correlation (coefficient = 0.603) among BI and AI, which indicates that students' intention to adopt AI tools positively leads to the adoption of AI tools. BI has an impact on Student Success (SS) as well (0.579), meaning that students who prepare to use AI tools are those who are likely to be successful at school. And that the adoption of AI tools positively inspires Student Success (coefficient = 0.333), meaning that the use of AI tools leads to better performance of students. Through the properly showing of Behavioral Intention, can increase the adoption of AI technology, and will eventually lead to the improvement of students' teaching experience and academic performance in higher education.

Conclusion

This study investigated the adoption of AI tools by students in higher education and how their use is related to academic performance outcomes. Results showed that students who use AI tools regularly, believe these tools are easy to use and believe these tools provide good value are more likely to continue using AI tools. Habit was the most common reason students continued using AI, followed by how useful and cost-effective they perceived the tools. Peer and teacher support, as well as good internet and tech support, also all contributed to encouraging AI use. The study found that students who exhibited a strong intention to use AI also adopted the tools more in practice, which also led to higher academic performance. This demonstrates how an open mind set about AI can translate into real outcomes in terms of learning. These insights hold particular significance for countries, like Pakistan, where digital access remains nascent. They teach us about how AI can be operationalized in environments that don't always have robust tech infrastructure. The study also contributes existing theories by demonstrating how behavior, support and habits relate to AI use and student success. For the universities and the teachers: the message is to keep AI tools easy, fun and integrated in the everyday learning. Provide that support to students, and they're more likely to use these tools in productive ways. Future research could examine how these findings hold in other countries, how teachers adopt AI, or how new AI tools affect learning over time. The bottom line is straightforward — when kids have support and the upside, AI can actually help them perform better academically.

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