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Bridging the gap: Factors influencing AI adoption in higher education institutions in Bangladesh

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Abstract

This study examines the key factors shaping stakeholders' (e.g., students, faculty members, and administrative staff within Bangladeshi universities) intentions and attitudes toward adopting artificial intelligence (AI) in Bangladeshi universities. To understand the drivers and inhibitors of AI adoption, we used two well-known models, Unified Theory of Acceptance and Use of Technology (UTAUT) and its updated version, UTAUT2, while also looking at factors like attitude, perceived risk, and the practical value of AI. Stratified random sampling is used to collect relevant data from public and private universities across major cities. Data collection involved a structured questionnaire designed with a 5-point Likert scale to measure constructs related to AI adoption as mentioned earlier. Our findings show that performance expectancy, hedonic motivation, utilitarian value, social influence, and facilitating conditions directly influence stakeholder attitudes and behavioral intention. Perceived risk and effort expectancy, however, do not significantly impact attitude. We consider attitude a strong predictor of behavioral intention, which is a key influencer of actual AI adoption in Bangladesh. These results provide actionable recommendations for policymakers, university leaders, and tech entrepreneurs who intend to develop a conducive environment for AI-led innovation in universities in Bangladesh.

Keywords: artificial intelligence (AI), higher education, AI adoption, behavioral intention, educational outcomes

Introduction

The revolutionary potential of artificial intelligence (AI) in higher education has attracted considerable interest among new technological developments. AI enhances various aspects of the educational experience by automating administrative tasks, delivering immediate feedback, and supporting personalized learning. AI-driven systems are revolutionizing education by facilitating personalized learning pathways, automating grading and other administrative tasks, and allowing for intelligent system-based tutoring all day and night (Baker & Inventado, 2014; Bessen, 2019).

In this context, Bangladesh, as a developing country, was officially recognized by the United Nations in 2021 for meeting the criteria for graduation from its Least Developed Country (LDC) status. The government of Bangladesh has already initiated efforts to develop the higher education system in both public and private universities. Therefore, to ensure and oversee progress in this area, the University Grants Commission was established in 1973 and is responsible for monitoring advancements in the higher education sector in line with the national education policy of 2010 and other government development plans related to higher education. These include the strategic plan for 2006, the updated comprehensive strategic plan for 2016-2026, the Sustainable Development Goals (SDGs) for 2015-2030, and the extension of the Strategic Plan for Higher Education 2018-2030. The vision of the most recent strategic plan (2018-2030) is to achieve excellence in higher education that meets global standards. However, the current global landscape has already established mechanisms for higher education institutions to enhance the quality of learning, teaching, and administration through modern technologies like AI. It is time for Bangladesh to integrate AI to improve its standing in global higher education.

Over the decades, Bangladesh has made remarkable progress in advancing higher education, with initiatives that boost the number of university students. This trend is expected to continue, as the proportion of youth with tertiary education is projected to rise from 11% in 2010 to 20% by 2035 (World Bank, 2019). In 2010, the Government of Bangladesh introduced a policy to enhance higher education, promote innovative knowledge, and develop human resources, aligning these efforts with the global demands for sustainable development (Ministry of Education, 2010). Consequently, a strategic plan was created under the vision of Digital Bangladesh, which has significantly advanced the country’s IT sector by prioritizing higher education (UGC, 2018). However, according to a report by Dhaka Tribune, not a single Bangladeshi university secured a position in the 2019 Asia University Rankings by Times Higher Education. However, six were listed in the QS Asia University Rankings, with Dhaka University placing 127th. Research has also shown that efforts are insufficient to achieve sustainable development in higher education, as every institution, including public and private universities, faces significant challenges (Chowdhury et al., 2020).

The principal obstacles that higher education is facing include a scarcity of initiatives, deficient financial and technological resources, inadequate proficiency in technological utilization, teachers' insufficient capabilities in system operation and student motivation, subpar internet connectivity, and the lack of an optimal learning environment (Roy et al., 2023). In addition, the state of research and higher education in Bangladesh is currently inadequate due to insufficient funding for research, lack of defined research goals, burdensome teaching responsibilities, high political interference in decision-making, absence of structured development frameworks, and a system where entry-level (lectureship) do not mandate doctoral degree, alongside a significant number of senior faculty lacking doctorates. Collectively, these issues degrade the quality of higher education in the country (UGC, 2018). As a result, a new pedagogical approach is essential to assist educators in designing and refining their courses, thereby offering a more comprehensive, holistic, and systematic sustainability education (Lozano et al., 2017; Hefferman & Hefferman, 2014).

While existing research offers insights into AI adoption across various contexts and sectors, a noticeable research gap persists, especially in higher education. In Bangladesh, explicit research on AI adoption remains scarce (Latif et al., 2021). The distinctive opportunities and challenges posed by AI in higher education in Bangladesh remain largely underexplored in existing research (Shirin, 2022; Sultana & Faruk, 2024). Consequently, this research endeavors to comprehensively address and close this evidence gap. The investigation centers on and examines critical factors that influence the application of AI, encompassing perceived risks, performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, utilitarian value, and behavioral intentions.

In this study, we have utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) and its extension, the UTAUT2 model (Venkatesh, Chan & Thong, 2012). The original UTAUT framework comprises four key constructs: Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI). PE and EE reflect the technological context, while FC and SI represent the implementation context (Schaper & Pervan, 2007). We excluded two additional constructs, Price Value and Habit, as Bangladesh is still in the early stages of technology adoption, making these constructs less relevant. From the UTAUT2 model, we have only incorporated the Hedonic Motivation (HM) construct, conceptualized as the perceived enjoyment of technology use (Thong et al., 2006).

Neither of the models explicitly considers the individual-level determinants of adoption. Given that students and teachers are the primary stakeholders in AI adoption in higher education, it is essential to consider factors relevant to the individual context. Therefore, we have integrated Attitude (ATT) as a mediating variable, a construct used in previous research (Alshare & Lane, 2011). Additionally, we have included two exogenous variables for a more comprehensive analysis: Perceived Risk (PR), representing stakeholders' risk-taking behavior (Lewis & Weigert, 1985), and Utilitarian Value (UV), which reflects extrinsic motivation for adopting technology.

These additions represent key contributions to our proposed theoretical model. Furthermore, Attitude (ATT) and Behavioral Intention (BI) are endogenous variables that significantly influence technology adoption. We did not involve any moderating variables, as their exclusion increases the model's explanatory power, which is another novel contribution of this research.

Our study finds that (i) Perceived risk (PR) and Effort expectancy (EE) have statistically insignificant effect on the attitude of stakeholders of higher education institutions towards the adoption of AI; (ii) Performance expectancy (PE) and Hedonic Motivation (HM) have significant effect on the attitude (ATT) of stakeholders of higher education institutions towards the adoption of AI; (iii) Utilitarian Value (UV) and Social Influence (SI) have significant and positive effect on the attitude of stakeholders of higher education institutions towards the adoption of AI; (iv) Facilitating Conditions (FC) has significant positive effect on the integration of AI; (v) Attitude has strong positive correlation with behavioral intention, and it also indirectly significantly affects the adoption of AI; (vi) Behavioral Intention (BI) has significant and positive relationship with the adoption of AI in higher education institutions.

The remainder of this paper is organized as follows: First, we review relevant literature and the theoretical framework for formulating hypotheses. Next, we describe the research methodology. We then discuss our empirical results regarding AI integration in higher education institutions in Bangladesh, followed by a discussion of our findings. Finally, we conclude by summarizing our key contributions, acknowledging limitations and suggesting future research in the relevant field.

Review of literature and theoretical framework

Artificial intelligence has created new opportunities and challenges in Bangladesh's higher education domain (Shohel et al., 2024). It has added value to educational sustainability, greatly supporting students, teachers, and administrative staff (Sultana & Faruk, 2024). In Bangladesh, AI applications in higher education enable students to interact with course content independently, thus minimizing the potential need for private tutoring (Khan et al., 2021). AI has proved effective and efficient in preparing graduates with the skills needed for their future careers in higher education (Alghaithi et al., 2022). Consequently, university teachers in Bangladesh have been showing a growing interest in incorporating AI into the higher education system (Shirin, 2022). AI tools can improve the quality of higher education, accessibility, personalization of learning, and research opportunities (Nipun et al., 2023).

The widespread adoption of online learning has further highlighted AI's capacity to improve instructional methods and learning outcomes (Ouyang et al., 2022). In advanced education, AI supports the evaluation of emerging trends and provides strategies to improve academic training and research (Ruiz et al., 2023). Despite this, research interest in AI has proliferated across various fields, putting into light our increasing reliance on these technologies and the expectation of an algorithmic future (Dogan et al., 2023). While acknowledging that AI improves teaching, learning, and academic administration, students are wary of its use in admissions, examinations, and placements (Kumar & Raman, 2022). Higher education institutions must prepare students for the AI revolution by equipping them with the essential skills of the future (Jain & Jain, 2019). Higher education in East Asia has had its regionalism and hybridization impelled by the double forces of modernization and globalization. At the same time, AI integration is critical in embracing global technologies in this region (Lo, 2016). The development of AI in education policy and governance reflects the broader historical context of how data and metrics have shaped educational systems (Piattoeva & Boden, 2020). AI now supports stakeholders in teaching, learning, and administrative tasks in higher education institutions (Chatterjee & Bhattacharjee, 2020).

In Bangladesh, the increased interest in AI in higher education indicates the growing willingness of stakeholders to implement these technologies. The literature on the impact of AI in higher education is extensive. However, a lack of research investigating the adoption and integration of AI within the higher education framework of Bangladesh is felt in the existing literature. There may be scattered opinions on the role of AI in Bangladeshi higher education. However, these insights can never suffice for a comprehensive view or assessment of the degree to which AI is integrated into this context. In addition, there is an almost complete lack of quantitative analysis regarding policies, strategic plans, practices, implications, attitudes, and behavioral intentions of stakeholders in these institutions. Against this backdrop, this study is essential for evaluating the effectiveness of AI in higher education in Bangladesh.

Key theories or concepts

Modern technology in determining individuals' adoption of innovations has been essential, as noted in information systems, sociology, and psychology models. Various theories explain this behavior. As noted by Davis (1989) through his Technology Acceptance Model (TAM), perceived usefulness and ease of use are among the key variables that drive people to adopt technologies. This is further extended by the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), which integrates performance expectancy, effort expectancy, social influence, and facilitating conditions to explain up to 70% of the variance in behavioral intention. This has been further extended by UTAUT2, the extension of the UTAUT, thus positioning

UTAUT as one of the most comprehensive models in IT acceptance studies, including AI.

Others include the Diffusion of Innovation (DOI) theory of Rogers (1962), which focuses on innovation characteristics; the Theory of Planned Behaviour (TPB) of Ajzen (1991), which focuses on attitudes and norms; and the Task Technology Fit (TTF) model proposed by Goodhue and Thompson (1995) that emphasized the fit between tasks and technology. Together, each of these frameworks forms a sound basis on which factors of user acceptance of new technologies can be evaluated. For an overall assessment of IT acceptance, UTAUT performs outstandingly well. On this line, Marangunić and Granić (2015) state this argument again, which has been articulated by Venkatesh et al. 2003, Venkatesh, Chan & Thong, 2012, and Xue et al. 2024. Thus, the UTAUT model could be seen as helpful in evaluating the success or failure of new technologies such as AI. Also, the UTAUT model is widely applied by various researchers to assess users' intention to adopt IT.

Theoretical framework and hypothesis development

The UTAUT, introduced by Venkatesh et al. (2003), represents a stronger explanatory capacity than other models in predicting technology acceptance behaviors. The UTAUT model comprises four core factors: Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence. For this study, we add 'Hedonic Motivation' from the UTAUT2 extension (Venkatesh, Chan & Thong, 2012) to capture additional motivational aspects. Stakeholders here are considered uniquely, as the adoption of AI involves significant governmental and organizational cost considerations. In the context of AI in higher education in Bangladesh, where adoption is at an early stage, we exclude constructs like Price Value and Habit.

We develop a holistic framework by consolidating constructs from UTAUT and UTAUT2 models. Our research posits that attitude mediates the influence of ‘Performance Expectancy’ and ‘Effort Expectancy’ on ‘Behavioral Intention’ (Alshare & Lane, 2011; Cox, 2012). We also retain 'Perceived Risk' as an exogenous construct, which previous research (Abu-Shanah & Pearson, 2009) identifies as crucial to explain AI adoption resistance. The facilitating conditions and hedonic motivation are posited to directly influence behavioral intention, consistent with Venkatesh, Chan & Thong (2012). Our conceptual framework thus puts forward the argument that perceived risk, utilitarian value, performance expectancy, effort expectancy, and hedonic motivation influence behavioral intention through attitude, while facilitating conditions directly affect behavioral intention. The following section clarifies these constructs and their measurable indicators for hypothesis development.

Perceived risk (PR)

Perceived risk, a concept related to user behavior, is linked to individual risk tolerance (Bauer, 1967) and strongly influences adoption decisions and behavioral intentions (Kim et al., 2008). The unpredictable nature of internet-based AI tools adds to users' behavioral insecurity (Zhang & Maruping, 2008), and high perceived risk (PR) can negatively impact users' attitudes (Susanto & Goodwin, 2011; Teo & Liu, 2007). Higher PR leads to more cautious attitudes toward adopting new technology (Habib & Hamadneh, 2021). Conversely, reducing PR through effective communication and risk management can improve attitudes and adoption intentions (Silva et al., 2023; Abbasi et al., 2024). Therefore, we hypothesize:

Hypothesis 1: Perceived Risk (PR) negatively affects users' Attitude (ATT) and Behavioral Intentions (BI) toward adopting AI in higher education.

Utilitarian value (UV)

Utilitarian value, emphasizing efficiency, convenience, and cost-effectiveness, strongly influences consumer attitudes and decision-making, particularly in public policy (Sunstein, 2020; Vining & Weimer, 2006; Frederiks et al., 2015). Studies in online shopping and healthcare sectors show that perceived utilitarian value fosters positive attitudes, increasing usage intentions (Louis et al., 2023; Gunawan & Sondakh, 2020). Within online learning, the functional advantages of platforms positively impact students' attitudes and intentions (Alam et al., 2022). Thus, we hypothesize:

Hypothesis 2: Utilitarian Value significantly and positively affects users' Attitude (ATT) and Behavioral Intentions (BI) towards adopting AI in higher education.

Performance expectancy (PE)

In the UTAUT model, Performance Expectancy (PE) relates to the belief that using a system will improve job performance, often influencing technology acceptance decisions (Venkatesh et al., 2003). Evidence indicates that positive expectations of a technology's benefits enhance users' attitudes and reinforce their intentions to adopt it (Raza et al., 2020). Therefore, we hypothesize:

Hypothesis 3: Performance Expectancy significantly and positively affects users' Attitude (ATT) and Behavioral Intentions (BI) towards adopting AI in higher education.

Effort expectancy (EE)

Effort Expectancy in UTAUT refers to the perceived ease of using a technology, where lower anticipated effort often leads to increased acceptance (Venkatesh et al., 2003). Research demonstrates that positive perceptions of effort expectancy influence attitudes, subsequently affecting adoption intentions (Chen et al., 2021; Tak et al., 2023; Maqsoom et al., 2024). Thus, we hypothesize:

Hypothesis 4: Effort Expectancy significantly and positively affects users' Attitude (ATT) and Behavioral Intentions (BI) toward adopting AI in higher education.

Social Influence (SI)

Social Influence in UTAUT refers to perceived social pressures to adopt a technology. Studies highlight its role in shaping attitudes and intentions, particularly when peer networks and social proof impact adoption decisions (Graf-Vlachy et al., 2018; Kavandi & Jaana, 2020; Fox & Connolly, 2018). We propose the following hypothesis:

Hypothesis 5: Social Influence significantly and positively affects users' Attitude (ATT) and Behavioral Intentions (BI) towards adopting AI in higher education.

Hedonic motivation (HM)

Hedonic Motivation, integrated into UTAUT2, captures the enjoyment of technology use, significantly influencing adoption, especially in non-work contexts (Venkatesh, Chan & Thong, 2012). Research demonstrates that intrinsic enjoyment of technology positively shapes attitudes and supports continued engagement (Salimon et al., 2017; Sitar-Tăut, 2021). We hypothesize:

Hypothesis 6: Hedonic Motivation significantly and positively affects users' Attitude (ATT) and Behavioral Intentions (BI) toward adopting AI in higher education.

Facilitating conditions (FC)

Facilitating Conditions encompass organizational and technical support for technology use, which strongly affects Behavioral Intentions (Venkatesh et al., 2003). Studies confirm that perceived adequate resources and support enhance adoption intentions (Rana et al., 2024). Hence, we propose:

Hypothesis 7: Facilitating Conditions significantly and positively affect users' Behavioral Intentions (BI) toward adopting AI in higher education.

Attitude (ATT)

Attitude is a critical determinant in technology adoption, with positive attitudes fostering acceptance and negative attitudes creating barriers (Davis, 1989). Studies affirm that attitude significantly shapes Behavioral Intentions (Chen et al., 2021; Cox, 2012). We hypothesize:

Hypothesis 8: Attitude significantly and positively affects users' Behavioral Intentions (BI) towards adopting AI in higher education.

Behavioral intentions (BI) and adoption of AI in higher education (AAHE)

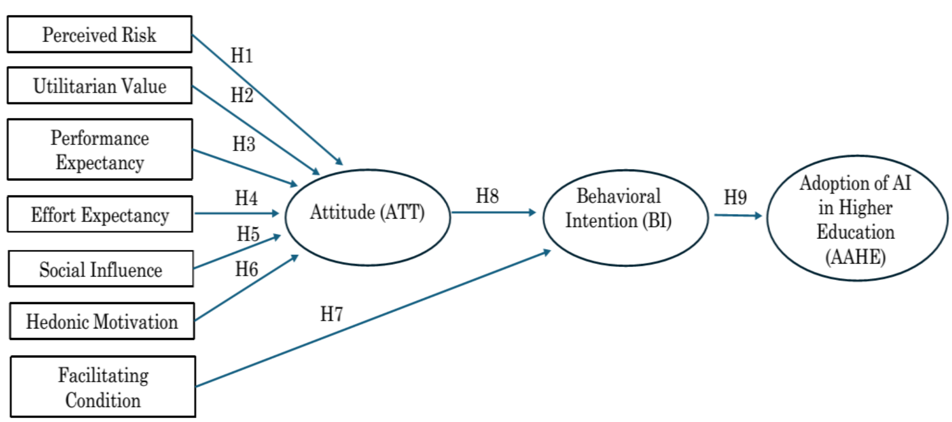
Behavioral Intention, a key predictor of actual behavior, mediates the relationship between attitudes and adoption (Sun & Zhang, 2006). Studies show that strong intentions facilitate technology acceptance, enhancing effective implementation (Amoako-Gyampah & Salam, 2004). We hypothesize:

Hypothesis 9: Behavioral Intention significantly and positively affects the adoption of AI in higher education (AAHE).

The Conceptual model

The study's analytical framework combines the UTAUT and UTAUT2 models with other relevant factors to address the research objectives. From the comprehensive analysis, we believe that the variables depicted in Figure 1 below are well-suited to the focus of our research. The model shows that perceived risk, utilitarian value, performance expectancy, effort expectancy, social influence, and hedonic motivation directly and significantly influence attitude.

Figure 1
Conceptual model (authors' creation)



These variables together form the behavioral intention to adopt AI in higher education. Further, the facilitating conditions have a direct and significant effect on AI adoption in higher education in Bangladesh; this evidence suggests that the existence of adequate resources and support is important in the given context.

Research methodology

Population, sampling, and sample size

The targeted population in this research involves those who have adopted AI in their educational platforms, specifically students and teachers in the higher education institutions of Bangladesh. This includes both public and private universities at various academic levels. To ensure proper representation, we randomly selected several prominent higher education institutions in five metropolitan cities: Dhaka, Rajshahi, Khulna, Chittagong, and Rangpur. The sampling method was stratified to have a more valid finding, and the population was divided into subgroups based on the university type: public, private, and specialized universities. The benefit of this is that it ensures that each subgroup is well-represented in the final sample.

The total target sample size is fixed at 600 participants, a number strong enough to obtain statistical power and guarantee the reliability and validity of the results (Cohen, 1988). First, we contacted 1,000 individuals from these institutions, targeting students and faculty members. From this outreach, we received 605 quantifiable responses using a 5-point Likert scale to assess various dimensions of AI integration in education. This robust sampling strategy enhances the credibility of the research findings and allows for a more detailed exploration of AI integration in higher education in Bangladesh.

Instrument design

This study utilized 48 measurement items distributed across nine constructs within the questionnaire. Each construct included multiple reflective indicators aligned with a multi-item measurement approach and adapted from established measures in the existing literature. While all measurement items were previously used in prior research, some were modified to better fit this study's specific context. This approach ensured that the constructs were both theoretically grounded and contextually relevant. The variables measured in the questionnaire include perceived risk, utilitarian value, performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, attitude, behavioral intention, and adoption of AI in higher education.

Perceived risk (5 items), adapted from Abu-Shanah and Pearson (2009), captures concerns about privacy, security, and potential AI misuse. Utilitarian value (4 items) drawn from Venkatesh, Chan & Thong (2012) assesses AI's functional benefits in education, such as improving efficiency and learning outcomes. Performance expectancy (5 items) derived from Alshare and Lane (2011) and Cox (2012) measures beliefs that AI will enhance educational performance. Based on the same sources, effort expectancy (5 items) evaluates the perceived ease or complexity of using AI in education. Social influence (3 items) from Venkatesh, Chan & Thong (2012) examines how participants perceive influence from significant others, like peers or institutional support, on AI adoption decisions. Hedonic motivation (5 items), also from Venkatesh, Thong & Xu (2012), focuses on the enjoyment of using AI, reflecting its motivational appeal. Facilitating conditions (5 items) based on Venkatesh Chan & Thong (2012) gauge the availability of resources and support, such as technology and training needed for AI use.

Attitude (5 items), adapted from Chong (2013), measures positive or negative feelings toward AI adoption. Behavioral intention (5 items) derived from Dwivedi et al. (2017) and Venkatesh et al. (2003) assesses the intention to adopt AI tools in educational practices. Finally, adopting AI in higher education (4 items) from Chatterjee and Bhattacharjee (2020) captures participants' actual or intended use of AI technologies in their academic activities.

Due to their limited relevance in the current research context, we have omitted the constructs, e.g., Price Value and Habit, as proposed in UTAUT2, from the model. In Bangladeshi universities, AI adoption initiatives are generally driven by institutions rather than individuals, meaning that faculty and staff are not directly involved in cost-related decisions, which makes Price Value less applicable. Furthermore, since AI tools are not yet widely embedded in daily academic routines, the development of automatic or habitual usage patterns is unlikely, making the Habit construct premature at this stage of adoption (Oliveira et al., 2016; Al-Emran et al., 2018).

Pilot test

Before the primary data collection, a pilot test involving 30 participants drawn from the target population was conducted. The primary objective of the pilot test was to assess the questionnaire items' clarity, relevance, and reliability (Teijlingen & Hundley, 2002). Participants provided feedback regarding their understanding of the questions, the relevance of the content, and any ambiguities they encountered. Analyzing this feedback allows researchers to pinpoint specific areas needing improvement and to make necessary revisions to the questionnaire based on participant responses (Teijlingen & Hundley, 2002). By refining the questionnaire through this process, we aim to ensure that the final instrument accurately reflects the theoretical constructs related to AI adoption in higher education.

Data analysis

We employed Structural Equation Modeling (SEM), which integrates two powerful statistical approaches: exploratory factor analysis and structural path analysis. Kock (2017) supports the use of SEM through Partial Least Squares (PLS) in studies similar to ours within the field of management science. Following Hair et al. (2017) guidance, we selected the appropriate SEM method, choosing PLS SEM over Covariance-Based (CB) SEM. PLS-SEM is especially advantageous for smaller sample sizes and for studies centered on theory development, which is the primary focus of our research.

Results and Discussion

Socio-demographic profile and AI usage of the respondents

This survey gathered data from 605 respondents nationwide to evaluate participants' socio-demographic characteristics, including age, gender, education, profession, field of study, and institutional affiliation.

Table 1

Socio-demographic profile of the respondents

Variable	Category	Frequency	Percent
Age Group	18-25	369	61.0
	26-35	179	29.6
	36-45	42	6.9
	46-49	8	1.3
	50-59	5	0.8
	60 and above	2	0.3
	Total	605	100.0
Gender	Male	341	56.4
	Female	264	43.6
	Total	605	100.0
Educational Qualification	Bachelor	361	59.7
	Master's	216	35.7
	PhD/Doctoral Degree	22	3.6
	Others	6	1.0
	Total	605	100.0
Academic Discipline	Arts	26	4.3
	Social Science	50	8.3
	Business Studies	301	49.8
	Engineering and Technology	108	17.9
	Sciences	68	11.2
	Computer Science and Information Technology	35	5.8
	Law and Legal Studies	13	2.1
	Agriculture	4	0.7
	Total	605	100.0
Types of Institutes	Public University	336	55.5
	Private University	269	44.5
	Total	605	100.0

The demographic analysis of the sample suggests some key characteristics of the 605 respondents: a majority (61.0%) are between 18 and 25 years old, which reflects a youthful demographic dominated mainly by undergraduate students. Gender distribution shows a slight male dominance, with 56.4% males and 43.6% females, suggesting a balanced representation. Most respondents hold a bachelor's degree (59.7%), while a smaller percentage hold a Master's (35.7%) or doctoral degree (3.6%). By field of study, the majority are Business Studies students (49.8%), followed by Engineering and Technology (17.9%) and Sciences (11.2%). It indicates that, overall, business-related fields of study are very strong. As for university ownership, 55.5% of the respondents were from public universities, an all-time high compared to private universities at 44.5%. This is an important demographic profile to understand the focus of the study on technology adoption in higher education, as it captures characteristics and experiences relevant to the study from a diverse student group.

Table 2

Usage areas and activities of AI in academic work

Usage Areas	Frequency	Percent
Research	209	34.5
Education	277	45.8
Administration	24	4.0
Others	7	1.2
Research and Education	69	11.4
All of them	19	3.1
Total	605	100.0

Table 2 shows AI's various usage areas and activities in academic work, highlighting its significant role across different domains. Most respondents (45.8%) indicated that AI is primarily utilized in education, enhancing personalized learning experiences, automating grading, and supporting intelligent tutoring systems. Research follows closely, accounting for 34.5%, as AI tools facilitate data analysis, literature reviews, and hypothesis generation, thereby improving research efficiency. In contrast, only 4.0% of respondents noted its application in administration, which may involve streamlining processes such as scheduling and admissions. A combined 11.4% of participants recognized AI's impact on research and education, reflecting the interconnectedness of these areas. Furthermore, a small segment (3.1%) stated that AI is utilized across all domains mentioned. Overall, the data underscores the transformative potential of AI in enhancing educational practices and research productivity while indicating areas for further growth, particularly in administrative applications.

Table 3

Usages of AI-based platforms

AI Tool/Platform	Frequency	Percent
Google AI	198	32.7
Open AI	195	32.2
DeepMind	16	2.6
Microsoft Research	38	6.3
Amazon Web Services	14	2.3
Google Cloud Platform	28	4.6
Open AI Universe	5	0.8
Humata AI	7	1.2
IBM Watson	5	0.8
Google TensorFlow	27	4.5
Open AI Gym	8	1.3
Others	33	5.5
I do not use any of them	31	5.1
Total	**605**	**100.0**

Table 3 presents data on the usage of various AI tools and platforms among respondents, highlighting the popularity of Google AI and Open AI, which account for 32.7% and 32.2%

of responses, respectively. These two platforms are nearly tied as the most frequently used resources for AI applications in academic work. Microsoft Research follows with 6.3%, while other platforms like Google Cloud Platform (4.6%) and Google TensorFlow (4.5%) are also utilized, though to a lesser extent. DeepMind and IBM Watson have relatively low usage rates of 2.6% and 0.8%, respectively. Additionally, 5.5% of respondents use other unspecified tools, and 5.1% do not use any AI tools. This distribution indicates a strong preference for widely recognized platforms such as Google and OpenAI in the academic community while also suggesting opportunities for increased adoption and awareness of other available AI tools.

Table 4

Usages of AI Tools

AI Tool/Platform	Frequency	Percent
Zotero	33	5.5
Scopus	35	5.8
QuickCales	10	1.7
Zenodo	9	1.5
EndNote	24	4.0
ReadCube	14	2.3
ResearchGate	74	12.2
Google Scholar	242	40.0
F1000Prime	1	0.2
arXiv	10	1.7
SJ Finder	5	0.8
Litmas	7	1.2
Others	15	2.5
I do not use any of them	126	20.8
Total	**605**	**100.0**

Table 4 presents various AI tools in scientific and technological solutions, revealing a clear preference for Google Scholar, which 40.0% of respondents utilize. This indicates its prominence as a primary resource for academic research and information retrieval. ResearchGate follows with 12.2%, suggesting its value as a networking and publication platform among researchers. Other tools, such as Scopus (5.8%), Zotero (5.5%), and EndNote (4.0%), are also used, albeit to a lesser extent, highlighting the diverse range of tools available for academic work. Conversely, 20.8% of respondents reported not using any of these platforms, indicating potential areas for outreach and education about available resources. Overall, the data underscores the dominant role of Google Scholar in the academic landscape while pointing to various supplementary tools that researchers may leverage for their scientific and technical inquiries.

Measurement and structural model analysis

Non-response bias

The data collection process occurred in two phases: the initial phase gathered 300 responses (early responses), followed by an additional 205 responses after a follow-up (late responses). To assess non-response bias, we followed the approach recommended by Armstrong and Overton (1977). We compared the first and last 25% of responses and found no statistically significant differences between them for any of the measured items ($p > 0.05$). Additionally, no notable differences were observed between early and late respondents' demographic profiles or response patterns. Thus, non-response bias does not pose a significant concern in this study.

Common method bias

Common method bias (CMB) can skew results in survey-based research (MacKenzie & Podsakoff, 2012), so several precautions were taken during instrument development to minimize this risk. The questionnaire was designed using clear and simple language to avoid misunderstandings. To further mitigate CMB, we employed a split-survey method (Conway & Lance, 2010), collecting data through two separate surveys. The participants in both surveys had similar profiles and were drawn from a consistent sampling frame, reducing the likelihood of bias. Harman's one-factor test also revealed that the first factor accounted for 46.32% of the variance, below the 50% threshold, confirming that CMB was not a significant issue in our data.

Model measurement

Validity: Table 5 and Figure 2 below present the convergent validity of multiple constructs related to the adoption of AI in higher education, showing key reliability and validity metrics for each construct and its associated items. The construct "Adoption of AI in Higher Education" (AAHE) shows a high degree of internal consistency, with item loadings ranging from 0.818 to 0.846, Cronbach's alpha of 0.848, composite reliability (rho_c) of 0.897, and an AVE of 0.686, indicating high reliability and convergent validity. Similarly, the "Attitude" (ATT) construct shows good reliability of alpha = 0.834 and rho_c = 0.889, and an AVE of 0.668. "Behavioral Intention" (BI) also shows good reliability figures (alpha = 0.880, rho_c = 0.913). Other constructs, including "Effort Expectancy" (EE) and "Facilitating Condition" (FC), continue to hold up strongly in terms of validity, each having alpha values over 0.87 and AVEs over 0.60. "Hedonic Motivation" (HM) is problematic: one item, HM4, has a loading of -0.234, indicating it probably should be rethought. Other constructs, such as "Performance Expectancy" (PE), "Perceived Risk" (PR), "Social Influence" (SI), and "Utilitarian Value" (UV), also show high reliability (alpha > 0.80) with AVE above 0.60. Discriminant validity reported in Table 6 uses the Fornell-Larcker criterion and identifies that each construct correlates more with its own items than with other constructs.

Table 5

Assessment of internal consistency and convergent validity

Constructs	Item	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Adoption of AI in Higher Education	AAHE1	0.829	0.848	0.850	0.897	0.686
	AAHE2	0.818				
	AAHE3	0.819				
	AAHE4	0.846				
Attitude	ATT1	0.803	0.834	0.834	0.889	0.668
	ATT2	0.828				
	ATT3	0.814				
	ATT5	0.678				
Behavioral Intention	BI1	0.812	0.880	0.884	0.913	0.677
	BI2	0.782				
	BI3	0.799				
	BI4	0.866				
	BI5	0.852				
Effort Expectancy	EE1	0.752	0.874	0.887	0.908	0.665
	EE2	0.805				
	EE3	0.856				
	EE4	0.847				
	EE5	0.814				
Facilitating Condition	FC1	0.779	0.871	0.877	0.906	0.660
	FC2	0.799				
	FC3	0.811				
	FC4	0.827				
	FC5	0.843				
Hedonic Motivation	HM1	0.808	0.734	0.805	0.879	0.785
	HM2	0.880				
Performance Expectancy	PE1	0.810	0.845	0.866	0.894	0.679
	PE2	0.816				
	PE3	0.687				
	PE4	0.762				
	PE5	0.829				
Perceived Risk	PR1	0.777	0.864	0.878	0.901	0.646
	PR2	0.784				
	PR3	0.808				
	PR4	0.833				
	PR5	0.814				
Social Influence	SI1	0.884	0.832	0.834	0.899	0.749
	SI2	0.874				
	SI3	0.838				
Utilitarian Value	UV1	0.781	0.840	0.845	0.893	0.676
	UV2	0.818				
	UV3	0.854				
	UV4	0.834				

Figure 2

Measurement model illustrating the relationships between constructs in the study

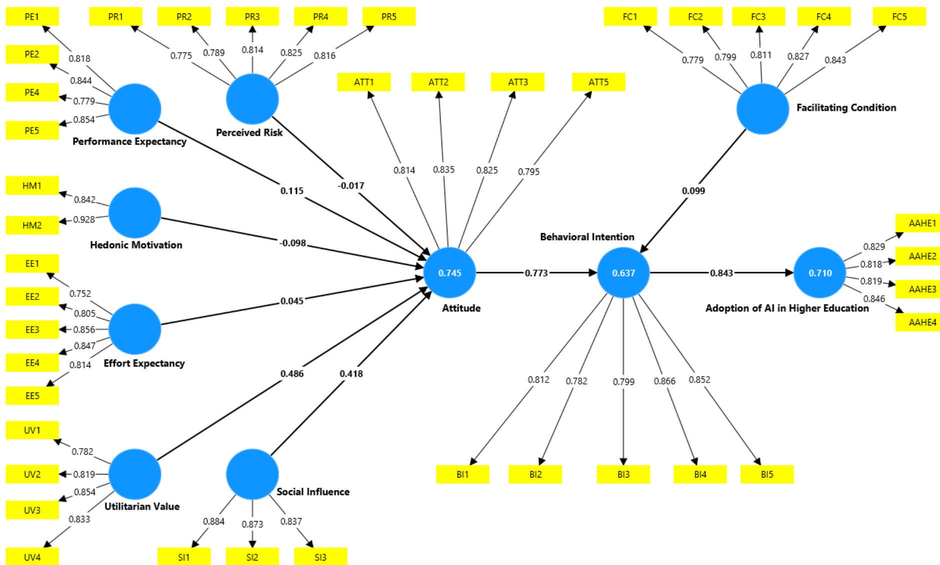


Table 6

Discriminant validity (Fornell-Larcker criterion, 1981)

Constructs	AAHE	ATT	BI	EE	FC	HM	PR	PE	SI	UV
AAHE	0.828									
ATT	0.823	0.817								
BI	0.843	0.792	0.823							
EE	0.251	0.229	0.229	0.815						
FC	0.238	0.187	0.244	0.807	0.812					
HM	0.208	0.153	0.206	0.649	0.824	0.886				
PR	0.191	0.169	0.202	0.727	0.853	0.806	0.804			
PE	0.254	0.234	0.260	0.800	0.835	0.738	0.789	0.824		
SI	0.830	0.796	0.784	0.201	0.222	0.184	0.180	0.219	0.865	
UV	0.760	0.809	0.698	0.173	0.169	0.153	0.136	0.159	0.752	0.822

AAHE = Adoption of AI in Higher Education; ATT = Attitude; BI = Behavioral Intention; EE = Effort Expectancy; FC = Facilitating Condition; HM = Hedonic Motivation; PR= Perceived Risk; PE = Performance Expectancy; SI = Social Influence; UV = Utilitarian Value.

The Fornell-Larcker criterion as reported in Table 6 is used to assess discriminant validity by comparing the square root of the average variance extracted (AVE) for each construct with its correlations to other constructs. Diagonal values (e.g., 0.828 for Adoption of AI in Higher Education) represent the AVE's square roots, which should be higher than any off-diagonal correlations to ensure constructs are distinct. For example, 'Adoption of AI' has a high correlation with 'Behavioral Intention' (0.843), but its diagonal value (0.828) confirms discriminant validity. 'Effort Expectancy' and 'Facilitating Condition' are closely related, yet distinct, as their diagonal values are higher than their correlations. 'Social Influence' has the highest discriminant validity, with a diagonal value of 0.865. Overall, Table 6 suggests that the study's constructs meet the Fornell-Larcker criterion, demonstrating that each construct is sufficiently distinct from others, a critical factor for the validity of a research model.

Structural model

Model Fit: The fitted structural equation model (SEM) is evaluated for collinearity (results available upon request), path coefficients, explanatory power (R-squared), and model fit using the standardized root mean square residual (SRMR) and normed fit index (NFI). The SRMR and the NFI are two commonly used indices to assess model fit.

Table 7

Model Fit Indices

Model	Saturated model	Estimated model
SRMR	0.046	0.060
d_ULS	1.807	3.117
d_G	0.972	1.124
Chi-square	3281.348	3584.425
NFI	0.825	0.809

In Table 7, the model fit indices compare the saturated and estimated models across several key measures, providing insights into the adequacy of the model fit. The Standardized Root Mean Square Residual (SRMR), a key indicator of model fit, is 0.046 for the saturated model and 0.060 for the estimated model, both falling below the recommended threshold of 0.08, indicating a good fit. However, the slightly higher value in the estimated model suggests marginally lower accuracy (Hu & Bentler, 1999). The discrepancy indices d_ULS and d_G, which measure the difference between observed and predicted covariance matrices, are higher for the estimated model (d_ULS=3.117, $d\_G = 1.124$) than for the saturated model (d_ULS=1.807, $d\_G = 0.972$), implying a less optimal fit. The Chi-square value for the estimated model (3584.425) is also higher than for the saturated model (3281.348), indicating a poorer fit. Additionally, the Normed Fit Index (NFI) for the estimated model (0.809) is slightly lower than the saturated model (0.825) and below the ideal 0.90 threshold (Bentler & Bonett, 1980), suggesting that while the model fit is reasonable, there is room for improvement in better capturing the data's structure. Overall, the estimated model shows an acceptable fit but could benefit from refinements to enhance its accuracy.

The structural model assesses the relationships between latent variables by analyzing key metrics such as path coefficients, t −values, and R^2 values. By applying the bootstrapping method with 5000 resamples, the model evaluates the significance of these relationships, offering insights into the constructs' predictive power (see Figure 1).

Table 8

R-squared

Constructs	R-squared	Adjusted R-squared
Adoption of AI in Higher Education	0.710	0.709
Attitude	0.745	0.743
Behavioral Intention	0.637	0.635

Assessment of R^2: The R^2 values and their adjusted counterparts for different constructs are reported in Table 7. The R^2 value indicates how well the independent variables explain variance in the dependent variable. While there are different ways to interpret R^2, Sarstedt et al. (2019) suggest that an R^2 of 0.13 is weak, 0.33 is moderate, and 0.67 or higher is strong. For 'Adoption of AI in Higher Education,' the R^2 value of 0.710 indicates that 71% of the variance in AI adoption is explained by the model's variables, with a slightly adjusted R^2 of 0.709 to account for model complexity. The 'Attitude' construct has an R^2 of 0.745, indicating 74.5% of its variance is explained, with an adjusted value of 0.743. Similarly, 'Behavioral Intention' has an R^2 of 0.637, showing 63.7% explained variance with a minor adjustment to 0.635. These values confirm the strong explanatory power of the model for each construct.

Hypothesis Testing: Following the guidelines of Hair et al. (2017), the bootstrapping technique with 5000 resamples was employed to determine the model's quality, focusing on metrics like R^2, beta coefficients, $t-$values, and $p-$values. Hypothesis testing was conducted using the bootstrapping method, providing both parameter coefficients and significance levels, all calculated at a 95% confidence interval (CI).

Table 9

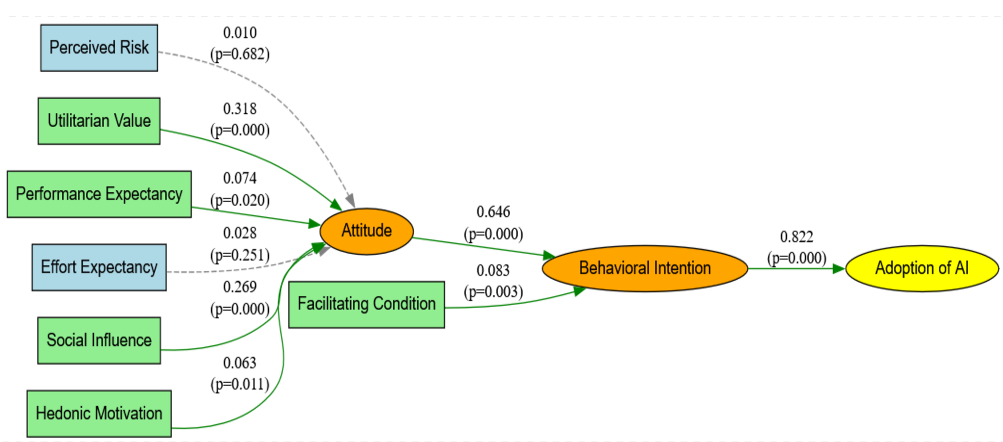
Analysis of Hypothesis Testing

Hypothesis	Hypothesized Relationship	Path coefficients	SD	*t*-value	*p*-value	Decision
H1	Perceived Risk > Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.010	0.026	0.410	0.682	Rejected
H2	Utilitarian Value > Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.318	0.033	9.658	0.000	Supported
H3	Performance Expectancy > Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.074	0.032	2.319	0.020	Supported

H4	Effort Expectancy > Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.028	0.025	1.149	0.251	Rejected
H5	Social Influence >Attitude >Behavioral Intention >Adoption of AI in Higher Education	0.269	0.037	7.280	0.000	Supported
H6	Hedonic Motivation > Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.063	0.025	2.555	0.011	Supported
H7	Facilitating Condition > Behavioral Intention > Adoption of AI in Higher Education	0.083	0.028	2.970	0.003	Supported
H8	Attitude > Behavioral Intention > Adoption of AI in Higher Education	0.646	0.032	20.196	0.000	Supported
H9	Behavioral Intention > Adoption of AI in Higher Education	0.822	0.017	48.384	0.000	Supported

Figure 3

Structural model showing the hypothesized pathways and their significance



The structural model analysis (Table 9 and Figure 3) reveals various significant relationships between the hypothesized constructs concerning the adoption of AI in higher education. Hypothesis H1, which suggests that perceived risk influences attitude and behavioral intention leading to AI adoption, is rejected ($\beta = 0.010$, $p = 0.682$), indicating that perceived risk does not significantly affect the adoption decision. On the other hand, hypotheses H2 and H3, related to utilitarian value ($\beta = 0.318$, $p = 0.00$) and performance expectancy ($\beta = 0.074$, $p = 0.020$), show a significant positive effect on AI adoption, highlighting that these factors significantly shape users' attitudes and intentions towards AI in academic settings. Hypothesis H4, which links effort expectancy to adoption via attitude and behavioral intention, is also rejected ($\beta = 0.028$, $p = 0.251$), suggesting that ease of use does not have a substantial effect on the adoption decision. However, the role of social influence (H5) proves to be crucial ($\beta = 0.269$, $p = 0.000$), affirming that peer and societal pressures play a significant role in shaping attitudes and intentions towards AI adoption. Additionally, hedonic motivation (H6) shows a significant effect ($\beta = 0.063$, $p = 0.011$), indicating that the enjoyment derived from using AI tools contributes to their adoption. Facilitating conditions (H7) also positively influence behavioral intention, leading to AI adoption ($\beta = 0.083$, $p = 0.003$). Finally, attitudes toward AI (H8) strongly drive behavioral intention ($\beta = 0.646$, $p = 0.00$), which in turn significantly predicts AI adoption (H9) with the highest path coefficient observed ($\beta = 0.822$, $p = 0.00$). Therefore, the results highlight that while risk and effort expectancy are less influential, utilitarian value, performance expectancy, social influence, facilitating conditions, and a positive attitude towards AI are key drivers in adopting AI technologies in higher education.

Discussion of findings

This study offers a comprehensive analysis of AI's role in higher education by assessing its applications and the numerous factors impacting its adoption. We highlight a paradigm change as stakeholders increasingly recognize AI's value across education, research, and administration, enhancing both training and research capacities (Ruiz et al., 2023; Chatterjee & Bhattacharjee, 2020). Key benefits include AI's support for human efforts, intrinsic motivation to engage with it, greater knowledge access, and improved learning environments, aligning with broader trends in educational technology's transformative role (Shirin, 2022; Latif et al., 2021; Chatterjee & Bhattacharjee, 2020; Khan et al., 2021). However, resistance remains due to gaps in skills, infrastructure, and ethical considerations which emphasize that successful adoption requires strong support systems (Jain & Jain, 2019).

The study's structural model analysis reveals that certain factors significantly influence AI adoption, while others deviate from traditional models. The rejection of Hypothesis H1 shows that perceived risks do not significantly affect attitudes or intentions toward AI, suggesting that anticipated benefits may outweigh risks (Hirunyawipada & Paswan, 2006;

Slade et al., 2015). Hypothesis H2, supported by the findings, shows that utilitarian value strongly influences AI adoption, aligning with Venkatesh, Thong & Xu (2012) and indicating users' preference for AI's practical benefits, such as workflow efficiency and enhanced support. Hypothesis H3 further emphasizes that performance expectancy drives adoption, where users who see AI as capable of improving learning outcomes are more inclined toward adoption, in line with Davis (1989) on technology's utility.

Interestingly, Hypothesis H4 found effort expectancy (ease of use) to be insignificant, a departure from Venkatesh et al. (2003), likely because users in higher education may prioritize performance benefits over usability (Sun & Zhang, 2006). Hypothesis H5 shows that social influence significantly impacts adoption, consistent with Ajzen's (1991) theory on social pressure, as peer support fosters AI acceptance in educational settings. Hypothesis H6 suggests that hedonic motivation modestly supports adoption, aligning with Venkatesh, Chan & Thong (2012), as enjoyment from AI enhances user engagement. Facilitating conditions (H7) support AI adoption by providing essential infrastructure and support, reflecting findings from Thong et al. (2006) on reducing barriers. The most substantial factor, attitude toward AI (H8), strongly predicts adoption intentions, consistent with Fishbein and Ajzen's (2010) theory on attitude's predictive power.

Hypothesis H9 shows that behavioral intention affects the use of AI in higher education. It also shows that social influence, attitudes, utility, and support networks play an essential role in fostering AI adoption in higher education. Even though these are beneficial aspects, putting them into practice is very hard. This is especially true in places where people do not know how to use technology or where the infrastructure is not very good. Prior studies demonstrate that adoption is hindered by inadequate technological resources, unreliable internet connectivity, and limited access to advanced AI tools (Jain & Jain, 2019; Khan et al., 2021). This is in line with what we found: adoption is greatly affected by facilitating conditions (H7), which means that the benefits of AI are mostly not being used because there is not enough infrastructure and institutional support. In addition, many educators and students lack sufficient digital skills to fully engage with AI-based platforms, thus creating a disconnect between availability and actual usage (Latif et al., 2021). This aligns with our findings that effort expectancy (H4) was insignificant, suggesting that usability alone is not enough if baseline digital literacy is lacking. Ethical dilemmas further complicate implementation, including data privacy concerns, algorithmic biases, and the potential for widening educational inequalities (Ruiz et al., 2023; Shirin, 2022).

Cross-cultural studies on AI adoption indicate that these obstacles and ethical challenges differ markedly between educational institutions in developed and developing nations. In affluent nations, like those in Europe and North America, the integration of AI is typically supported by robust infrastructure, sophisticated digital ecosystems, and well-defined data governance frameworks (Venkatesh, Chan & Thong, 2012; Chatterjee &

Bhattacharjee, 2020). On the contrary, in developing regions such as parts of Asia and Africa, restricted internet access, poor institutional finance, and insufficient training programs provide significant challenges (Latif et al., 2021; Khan et al., 2021). Our results correspond with these trends as we found utilitarian value (H2) and performance expectancy (H3) to be crucial determinants of adoption, indicating that when resources are accessible and AI clearly improves education and research, adoption is more probable. Nonetheless, effort expectancy (H4) and perceived risk (H1) are not statistically significant. This may indicate a broader context in which surmounting structural and literacy obstacles is essential prior to the influence of usability or risk perceptions on attitudes.

Our study indicates that risk and usability concerns are comparatively less significant; however, utilitarian value, performance expectancy, social impact, and conducive settings, alongside a positive mindset, are crucial. These insights provide actionable directions for educators, policymakers, and developers to prioritize user attitudes, AI's utility, social support, and foundational resources, thereby fostering an environment conducive to sustained AI integration in higher education worldwide.

Conclusions

Education is essential to shaping a capable future workforce, and it requires modernized curricula, innovative teaching methods, and strategic technology integration. In Bangladesh’s higher education sector, AI holds promise for transforming teaching, learning, and administration. This study offers a model to support AI adoption, underscoring the benefits institutions may realize. Since education remains deeply human-centric, a balanced approach to AI and human involvement is crucial. Findings emphasize that AI-driven personalized learning can enhance engagement, though limited exposure to AI's benefits affects stakeholders' attitudes. This suggests a need for broader AI trials to demonstrate its positive impact on education. Over time, ease of use may become a more prominent factor in AI adoption as awareness grows.

Theoretical implications

This study employs the UTAUT model (Venkatesh et al., 2003) and its UTAUT2 extension (Venkatesh, Chan & Thong, 2012) to assess AI adoption in higher education. The original UTAUT model includes Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI), with PE and EE focused on technology and FC and SI on implementation (Schaper & Pervan, 2007). Constructs like Price Value and Habit are excluded because Bangladesh is still in the early stages of tech adoption. Drawing from UTAUT2, Hedonic Motivation (HM), or perceived enjoyment of technology, was added (Thong et al., 2006). Recognizing the unique context, Attitude

(ATT) was included as a mediator, backed by prior research (Ashare & Lane, 2011), along with Perceived Risk (PR) to gauge risk tolerance (Lewis & Weigert, 1985) and Utilitarian Value (UV) for extrinsic motivation, excluding moderating variables allowed for more substantial explanatory power, offering a nuanced understanding of factors influencing AI adoption in Bangladesh's higher education.

Practical and policy implications

The findings highlight Attitude as a key mediator in AI adoption in Bangladeshi higher education. Positive attitudes significantly influence Behavioral Intention to adopt AI, suggesting that higher education authorities should focus on shaping stakeholders' attitudes toward technology (H9). Performance Expectancy and Effort Expectancy emerge as major antecedents of Attitude (H3 and H4), underscoring the importance of AI's utility and ease of use. Developers should focus on intuitive, user-friendly designs, and authorities should support this with clear communication about user needs, including product brochures, success stories, and live demonstrations (Alshare & Lane, 2011; Dwivedi et al., 2015).

Policy recommendations include improving infrastructure, particularly in rural areas, to bridge the digital divide. Ongoing training and development for educators are critical to AI adoption success, and curricula should evolve to include AI across various fields, preparing students for a tech-enabled future. Ethical guidelines and data privacy standards are necessary to protect student data, while policies should also focus on inclusivity to ensure equitable access to AI-driven education. Collaborations with industry and global partners will enable institutions to stay at the cutting edge of AI advancements, offering students hands-on learning opportunities. Thoughtful planning is essential for maximizing AI's benefits and addressing its challenges, ensuring positive outcomes for all stakeholders in Bangladeshi higher education.

Limitations and future research

This study provides significant insights into the determinants influencing AI adoption in Bangladeshi institutions, but it possesses some limitations. First, the results we have obtained in this study may not be entirely applicable to other institutional or cultural contexts because it was only carried out in Bangladesh. To obtain a better understanding, Second, the model we use ignores the potential moderating effects of demographic variables such as age, gender, and academic discipline that could affect stakeholders' perceptions and adoption behaviors. We believe that inclusion of these factors in future studies could improve our understanding of the AI adoption process. Lastly, we used self-reported data, which could contribute to answer bias, including wanting to look good or not comprehending the questions. Future studies could be improved by using a variety of methods or adding measurable, objective data about how people really act to back up what has already been found and make things more straightforward.

Moreover, this research is concentrated mainly on individual-level constructs derived from the UTAUT and UTAUT2 frameworks. Subsequent research may explore the incorporation of organizational or institutional elements, such as leadership endorsement, digital infrastructure, and policy preparedness, that could profoundly influence AI adoption results. Adding these kinds of contextual variables to the model could help us understand the adoption landscape better. Our final suggestion for future research is to use qualitative methods like interviews or focus groups to add to the quantitative results. We believe that this way of analysis gives us a better understanding of what users are worried about, what drives them, and what constraints institutions face.

Abbreviations

UTAUT: Unified Theory of Acceptance and Use of Technology; PE: Performance Expectancy; EE: Effort Expectancy; FC: Facilitating Conditions; SI: Social Influence; HM: Hedonic Motivation; ATT: Attitude; PR: Perceived Risk; BI: Behavioral Intention; UV: Utilitarian Value; DOI: Diffusion of Innovation; TAM: Technology Acceptance Model; TPB: Theory of Planned Behavior; TTF: Technology Fit; AAHE: Adoption of AI In Higher Education; SEM: Structural Equation Modeling; PLS: Partial Least Squares; CB: Covariance-Based; LDC: Least Developed Country; SDGs: Sustainable Development Goals.

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Nilufa Akter (Conceptualization, Data curation, Formal Data Analysis, Methodology, Writing – original draft).
Md. Solaiman Chowdhury (Conceptualization, Supervision, Writing – review & editing).
Md. Mehedi Hasan (Writing – review & editing, Supervision).
Iqbal Hossain Moral (Writing – review & editing, Validation, Visualization).
Md. Shibley Sadique (Writing – final draft, Visualization, Project Administration).

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Data availability

The data used in this study were collected via a questionnaire and are not publicly accessible due to proprietary restrictions. The corresponding author can provide further details regarding data and any data requests.

Ethics Approval Statement

All procedures performed in this study involving human participants were in accordance with the ethical standards of the University of Rajshahi. Informed consent was obtained from all individual participants.

Declarations

Conflict of Interest Disclosure

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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