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EXAMINING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION USING UTAUT MODEL

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ABSTRACT

Artificial intelligence (AI) has created new potential as well as challenges for India's higher education system. The implementation of AI will result in a significant transformation of governance throughout Indian higher education institutions' internal architecture. The potential application of AI in education involves research into how students might learn, how teachers could improve their teaching, and how higher education institutions could make quick and accurate choices. This is significant since the massification of higher education has resulted in an increase in workload. Considering this situation, AI assistance is absolutely necessary. From this perspective, integrating AI into higher education is an important subject. Investigating how stakeholders could accept it is the aim of this study. To help with this, we used adoption theories and models, including the "Unified Theory of Acceptance and Use of Technology" (UTAUT) model. We were able to use a survey to validate our conceptual model and set of hypotheses with the help of responses from 150 respondents. It has been revealed that the model can assist policymakers in simplifying the integration of AI in higher education.

1. INTRODUCTION

The integration of AI technology with traditional teaching methods is a key element of Artificial Intelligence in Education (AIED), a field that reflects (or automates) educational practises and assumptions. (Holmes et al., 2023) India's higher education system has seen a dramatic expansion in the last 20 years. Certain scholars believe that private sector initiatives are to blame for this trend. Others believe that these projects are inadequate, half-baked, and exploitative. It has brought down the whole Indian higher education system. (Chatterjee & Bhattacharjee, 2020a) Artificial intelligence (AI) applications based on machine learning are proliferating in a variety of contexts, including education, agriculture, and medicine. There is a great deal of potential for using these apps in many contexts. Certain barriers stand in the way of precise applications, advantageous results, and higher degrees of achievement when utilising

AI in educational settings. (Nasar et al., 2023) There is insufficient information and inconsistent results about how AI affects learners writing abilities. However, the use of AI has been largely disregarded at the institutional level. (Alhumaid et al., 2023) Learning, learning success, learning domains, and learning approaches are all significantly impacted by artificial intelligence. The distinctive qualities of every learner are also crucial. The effectiveness of learning experiences is one benefit of integrating AI technology into educational systems. In addition to the university's anticipated value and relative benefit, students must be happy, love it, and have support from it in order to engage in an effective learning environment. (Dhir et al., 2023) Student engagement will rise if organisations and society recognise the value of incorporating these cutting-edge technologies into the classroom. Students' readiness to embrace new, cutting-edge technologies is influenced in certain nations by the hardware and software used in the classroom. Students with good problem-solving and critical thinking abilities may help facilitate the future adoption of new applications of artificial intelligence.(Zheng et al., 2023) Lower learning anxiety, a willingness to employ those technologies, and knowledge accomplishments are other factors that heavily influence students' views on adopting innovative technology. Prior research's primary goal was to develop a concept of adoption at the microlevel. In contrast with earlier studies, this one looks into the macro-level adoption of AI. The growing impact of AI on a variety of fields, including engineering, medicine, agriculture, and others, has been examined in earlier research.(Alhumaid et al., 2023)

Artificial intelligence can help customise learning. It can meet the unique requirements of every type of student. It would be wonderful to provide each student with a brand-new, distinctive instructional strategy that is catered to their own needs. Higher education institutions may benefit from improved learning environments because of AI-powered libraries.(Alhumaid et al., 2023) AI may be useful in this kind of individualised, customised learning. A variety of AI applications could support individualised learning. (Mangundu, 2023a) It's possible that AI technology isn't going to be ready for such an experience and that advancements will take longer. Chatbots can offer individualised assistance in resolving any pressing problem. It can offer answers to meet the demands of certain students. As AI-enabled chatbots advance in technology, they may be able to accurately respond to specific questions from students.(Shokeen et al., 2023) Students can get answers from these AI-powered chatbots outside of scheduled lesson times. This type of AI-powered system can also assist with student admissions inquiries, administrative decision-making, and other tasks. "Smart content" preparation may benefit from the application of AI technology. (Mangundu, 2023b) Digital textbook aids and adaptable digital learning interfaces for all educational levels could be examples of this. AI provides a lot of potential advantages for higher education. (Tsui et al., 2023) Because of the massification of students, there is an increase in workload. At this point, applying cutting-edge technology like artificial intelligence is necessary to address this concerning circumstance. (HALI & ELHAOUD, 2023) But until stakeholders—faculty, staff, students, and administrative personnel—adopt AI, it won't be helpful. On the other hand, it appears that not much research has been done on the use of AI in Indian higher education.

2. LITERATURE REVIEW

AI has given India's university system both new chances and challenges.(Silander & Stigmar, 2019) Artificial intelligence has created several opportunities to enhance governance in a more effective and efficient manner. Artificial intelligence (AI) in Indian higher education can be defined as computer systems that perform human-like tasks, including learning, adapting, synthesising, correcting, and utilising a variety of data required for complicated task processing. (Popenici & Kerr, 2017) Higher education needs AI support, as it is expected to be tremendously beneficial to researchers, professors, administrators, and students. (Chatterjee & Bhattacharjee, 2020b) As a result, it's essential to motivate the stakeholders to use this cutting-edge technology (AI), which is expected to improve India's higher education system altogether. The governments of all developed and developing nations are interested in raising the standard of education. AI and other contemporary technologies can be used to accomplish this. AI apps would update the evaluation system and track students' progress in learning. This helps the students learn from their current location.(Norris & Phillips, 2003) Governments all over the world are investing more money in expanding higher education by leveraging modern technologies. This will help elevate expectations for higher education through the application of AI. Learning in AI-supported environments is consistently superior to learning in traditional teacher-centric settings, as demonstrated by a plethora of studies. Additionally, AI is being employed increasingly often in Indian higher education institutions. As a result, the stakeholders would be motivated to use AI. The question is, how can we link the acceptance attitude of potential consumers with this? We are aware that one of the main research topics in current information technology literature is users' acceptance of modern technological advances. (Nasrallah, 2014) (Scicluna et al., 2012) The interest of potential users in employing cutting-edge technology like artificial intelligence is explained by a plethora of ideas and concepts. The disciplines of information systems (IS), psychology, and sociology serve as the foundation for these theories and models. Researchers found a lot of comparable elements when synthesising user acceptance behaviour from a variety of previous theories and models. Typically, they select the model or models that best fit the research question, ignoring the contributions of other theories and models. While other models and theories could only account for 17% to 53% of the diversity in behavioural intention, the UTAUT model was able to explain over 70% of the variation with the same set of data.(Chatterjee & Bhattacharjee, 2020a) Hence, it is thought that the UTAUT model can be used to understand people's intentions when it comes to accepting new technologies like AI. This model was modified by numerous researchers, who included new constructs appropriate for their research environment and omitted others. They have had successful outcomes.

3. CONCEPTUAL MODEL AND HYPOTHESES

The literature review research indicates that for similar data, the UTAUT has greater explanatory power than alternative theories or models. (Chatterjee & Bhattacharjee, 2020a) The UTAUT model is composed of four independent variables: performance expectation, effort expectation, social influence, and facilitating factors. We have excluded constructs like social influence and effort expectation from our analysis. Its two constructs, namely performance expectation and facilitating conditions, have been examined. Additionally, the inclusion of eight other existing models in the UTAUT model is another important factor in the selection of this model. The integrated constructs of UTAUT have provided a characterization of the constructs used in previous models. In this regard, it is seen as an all-inclusive paradigm for integrating participants acceptance, attitudes, and behaviours with AI adoption.(Chatterjee & Bhattacharjee, 2020a) It is evident that attitudes have been extensively recognised as a means of evaluating users' intentions for adopting technology. Many studies examined attitudes as mediating factors between relative advantage, facilitating conditions, and behavioural intention, as well as between behavioural intention and performance expectation.(Cox et al., 2019) Another new construct Relative advantage is included in this study as an independent variable.(Alhumaid et al., 2023) Thus, we theorised that behavioural intention is influenced by performance expectancy and relative advantage, which are mediated through attitude. It is suggested that there is a direct correlation between the facilitating condition and behavioural intention, as supported by other research.(Chatterjee & Bhattacharjee, 2020a) This would impact how artificial intelligence is used in the classroom. Even though we used the UTAUT paradigm, we neglected to take voluntariness, age, gender, and experience into consideration as moderators. This is due to the fact that our main goal is to interpret the direct correlations between the independent variables and behavioural intention and attitude. We think we have been able to provide evidence for the elements we selected to explain the adoption of AI in higher education (AAHE), which are performance expectation (PE), facilitating condition (FC), relative advantage (RA), attitude (ATT), and behavioural intention (BI). The conceptual model is shown in Fig. 1.

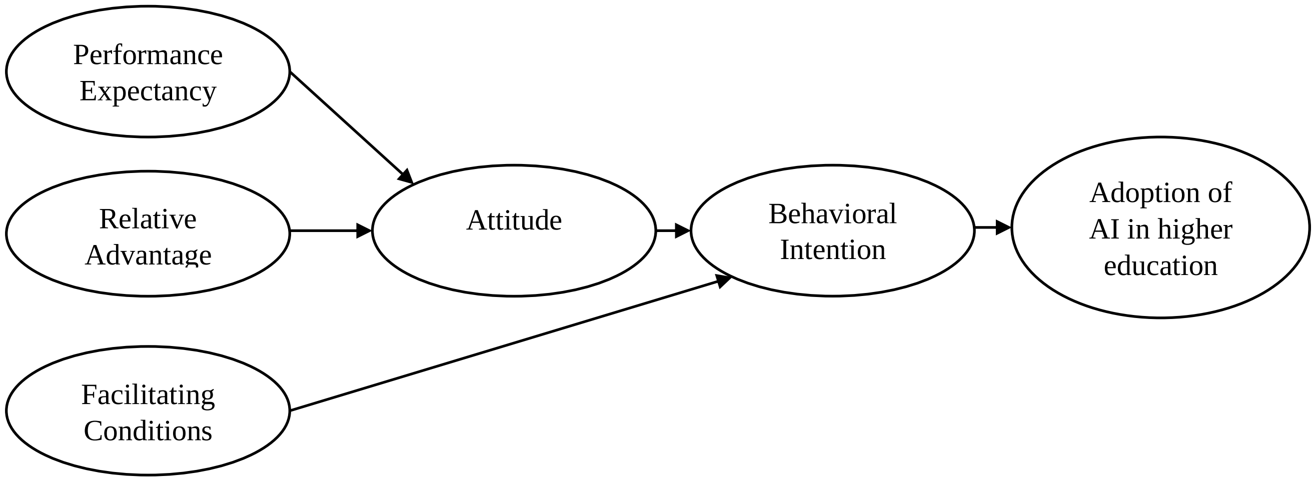

Fig 1: Conceptual Model

We will now attempt to explain each of the constructs independently as we continue to create the model and hypotheses.

3.1 PERFORMANCE EXPECTANCY (PE)

It is thought to represent the degree to which a user feels that utilising new technology would improve his or her performance at work significantly. It is widely accepted that performance expectancy is equivalent to perceived usefulness, outcome expectancy, and relative advantage. These presumptions have been used in prior adoption theories. Perceived utility and performance expectancy (PE) are interchangeable words. It significantly improves attitude in a favourable way (ATT). (Cox et al., 2019) (Lin et al., 2011) Following their consideration, the following theory is established:

H1: Performance expectancy (PE) has a significant impact on the attitude (ATT) of users towards adopting AI in higher education.

3.2 RELATIVE ADVANTAGE (RA)

The extent to which an innovation is viewed as more commonplace or superior to the idea it replaces is known as its relative advantage. "Relative advantage" is used in numerous studies on the transmission of innovation, and it effectively captures many of the salient characteristics of innovation. Relative advantage, which may be defined as the ratio of expected costs to expected gains, is one of the most accurate indicators of innovation resistance, according to Rogers. Furthermore, relative advantage—which Frambach and Schillewaert both agree is the best indicator of innovation adoption and resistance—is the best way to assess an organisation's level of innovation adoption, particularly when adopting an innovation over alternatives is crucial to the efficiency of the organisation's operations.(- & -, 2016)

H2: Relative Advantage (RA) has a significant impact on the attitude (ATT) of users towards adopting AI in higher education.

3.3 FACILITATING CONDITIONS (FC)

It might be defined as the degree to which a person thinks that the technical and financial infrastructure required to make the new system easier to use is actually available. The feeling Things like compatibility with other models and a sense of control over behaviour are examples of facilitating situations. It is becoming more and more clear that facilitating conditions (FC) and behavioural intention (BI) are related. Empirical data indicates that facilitating conditions (FC) have a major impact on behavioural intention (BI) when it comes to individual technology adoption. It has been noted that the Facilitating Conditions (FC) had a considerable impact on how US taxpayers' behavioural intentions (BI) were interpreted when they filed electronically. (Lee & Lin, 2008) (Schaupp & Carter, 2010) In light of these conversations, the following theory is proposed:

H3: Facilitating Conditions (FC) has a significant impact on Behavioural Intention (BI) of the users in Adopting AI in Higher Education.

3.4 ATTITUDE (ATT)

People communicate their emotions—whether happy or negative—in order to fulfil their desires, and this takes care of their attitude. The Theory of Technology Acceptance Model (TAM) states that an individual's attitude towards using a system determines their behavioural intention (BI). (Davis, 1989) Behavioural intention (BI) can be explained by attitude (ATT), as numerous prior studies have shown. ATT is a crucial mediating variable. Several research findings provide evidence in favour of this analysis. (Hung et al., 2009) Based on all of these inputs and after taking into account how attitude (ATT) affects users' behavioural intention (BI) while implementing AI in higher education, the following hypothesis is developed:

H4: Attitude (ATT) of individuals in adopting AI in higher education has a significant impact on Behavioural Intention (BI) of the users.

3.5 BEHAVIORAL INTENTION (BI) AND ADOPTION OF AI IN HIGHER EDUCATION (AAHE)

The process of assessing each person's contextual intention to engage in a certain activity is referred to as "behavioural intention" (BI). A reliable indicator of whether the expressed actions will actually manifest as the anticipated behaviours is this behavioural intention (BI). In this case, BI is used as a mediating variable to successfully influence behaviour to support the stated activity. (Nasrallah, 2014) The following theory is formed in part by the literature already mentioned:

H5: *Behavioural Intention (BI) of the users has a significant effect on Adopting AI in Higher Education (AAHE)*

4. RESEARCH METHODOLOGY

The conceptual model is displayed in Fig. 1 after an in-depth discussion of the model's development and an explanation of the procedures used to formulate the hypothesis. The hypotheses must be tested, and the conceptually developed model must be validated using the appropriate techniques. PLS-SEM analysis has been used to validate the conceptual model and its underlying assumptions. A questionnaire with six constructs, including 27 statements, was prepared. Data has been collected from postgraduate students of a famous university in Tamil Nadu through a survey questionnaire. A sample size of 150 responses has been received, which is used for the study.

5. RESULTS AND DISCUSSIONS

5.1 RELIABILITY AND CONVERGENT VALIDITY

Table 1: Construct Reliability and Validity

	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	.859	.779	.621
AAHE	.742	.771	.640
BI	.772	.732	.596
FC	.806	.736	.533
PE	.771	.740	.596
RA	.747	.779	.599

Every construct in Table 1 has a composite reliability rho_a value greater than 0.7, indicating internal item consistency among the constructs. Additionally, the composite reliability rho_c values are above 0.7, indicating internal consistency among the constructions. The consistency between the constructs is also shown by the values of AVE, which are greater than 0.5.

5.2 STRUCTURAL EQUATION MODEL

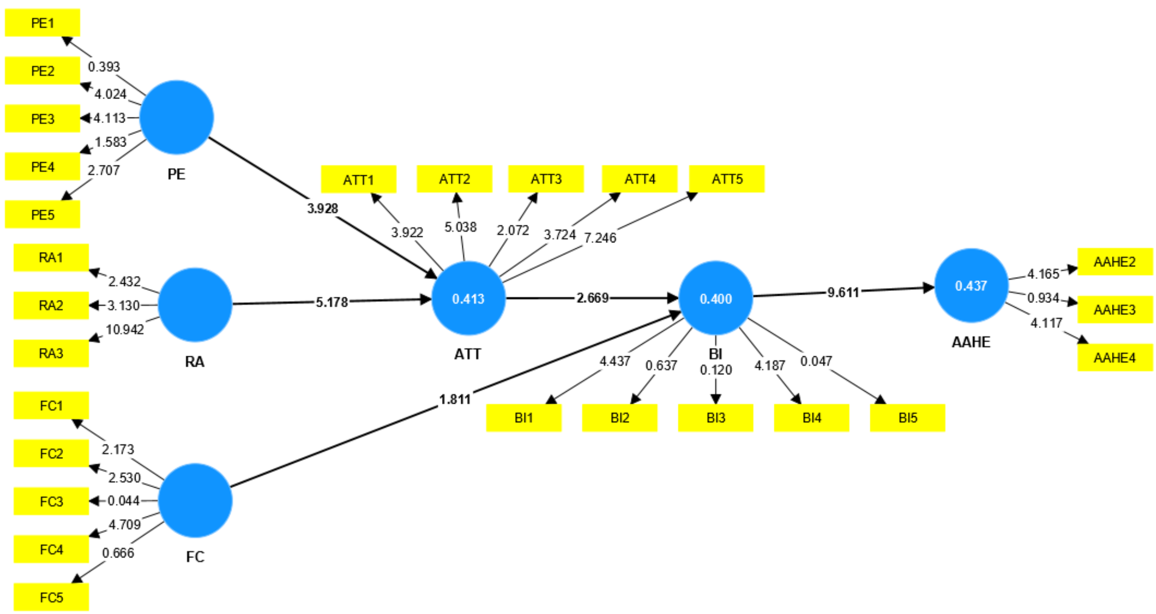

Table 2: Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT -> BI	.393	.363	.147	2.669	.008
BI-> AAHE	.661	.653	.069	9.611	.000
FC-> BI	.337	.428	.186	1.811	.070
PE -> ATT	.365	.384	.093	3.928	.000
RA -> ATT	.401	.417	.077	5.178	.000

Below is a discussion of each hypothesis's path coefficient. The hypotheses proposed are empirically supported by Figure 1 and Table 2. Performance Expectancy (PE) shows a significant effect on attitude (ATT) at o = 0.365, t = 3.928, and p = 0.000, which confirms H1. Relative Advantage (RA) shows a significant effect on attitude (ATT) at o = 0.401, t = 5.178, and p = 0.000, which confirms H2. Facilitating conditions (FC) don't show a significant effect on behavioural intention (BI) in this study. Attitude (ATT) shows a significant impact on the behavioural intention (BI) of users at o = 0.393, t = 2.669, and p = 0.008, which supports H4. Behavioural intention (BI) shows a significant effect on the adoption of AI in higher education (AAHE) at o = 0.661, t = 9.611, and p = 0.000, which supports H5.

5.3 MEDIATION ANALYSIS

Table 3: Specific Indirect Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FC->BI->AAHE	.223	.271	.100	2.226	.026
PE->ATT->BI	.143	.138	.063	2.284	.022
RA->ATT->BI->AAHE	.104	.101	.051	2.024	.043
PE->ATT->BI->AAHE	.095	10.092	.046	2.079	.038
ATT->BI->AAHE	.260	.243	.110	2.364	.018
RA->ATT->BI	.157	.151	.070	2.249	.025

"Mediation analysis examines the direct and indirect pathways through which an independent variable X affects a dependent variable Y through one or more mediator variables". Table 3 shows significant specific indirect effect on the variables used in the study. All variables used in this study possess significant specific indirect effect on other variables.

6. LIMITATION AND CONCLUSION

We have provided a model with strong explanatory power in this study; however, it is hard to deny that there are some specific shortcomings: India's use of AI in higher education is still in its infancy; we were able to obtain 150 valid responses from the survey; to gather data from actual users of AI in higher education, we need to expand the model by adding at least one more concept, "actual use." Furthermore, there was still room to impose additional limitations on the application of AI in higher education; these were concepts similar to "image," "output expectancy," and so forth; since they weren't taken into consideration, these were ignored. The proposed model has to be revalidated with these factors included to gather data from real users of AI in higher education. Future researchers will have to address these points. Future studies will include longitudinal time and longitudinal data, which could lead to a more generic representation of the model. With the assumption that the four moderators in UTAUT will not have an impact on the literate stakeholders in this setting, we employed the UTAUT model for assistance. It is not true that the results of our theoretical model would be completely undermined if the impacts of these moderators were ignored. But since we haven't employed the UTAUT model in its entirety, it can be seen as a limitation. These moderators may be used by future researchers to see if there is any way to improve the outcome. Our results demonstrate how important attitude is to reaching the study's objective. This component serves as a crucial mediator. Although artificial intelligence (AI) is still in its infancy, people's behavioural intentions to use AI in higher education in India are significantly influenced by the "attitude" variance. Our research has looked into the possibility of using AI in higher education, and our model identifies the factors that would encourage and facilitate the integration of AI in higher education. We have stated that there would be major advantages to higher education institutions implementing AI. It must be remembered once more that education is primarily a human activity. In essence, it is not reliant on technological solutions. Education is viewed as a problem that is primarily human. The intended outcomes in education would not be achieved by solely depending on technology.

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