Journal of Higher Education Theory and Practice
(ISSN: 2158-3595)
https://johetap.com/

QUANTITATIVE ASSESSMENT OF ARTIFICIAL INTELLIGENCE INTEGRATION IN HIGHER EDUCATION: A STRUCTURAL EQUATION MODELING STUDY

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ABSTRACT
The use of Artificial Intelligence (AI) in higher education in India has brought up new opportunities as well as difficulties. The implementation of AI is expected to result in substantial alterations to the governance framework of Indian higher education institutions. The potential applications of AI cover the exploration of educational consequences, including the enhancement of teaching methods, the acquisition of knowledge by students, and the facilitation of timely and accurate decision-making within educational institutions. This is especially critical because of the heightened workload stemming from the extensive growth of higher education. In light of this situation, the utilisation of AI is considered extremely necessary. The integration of artificial intelligence (AI) in higher education is a crucial matter in tackling these difficulties. The objective of this study is to explore the optimal methods by which stakeholders can successfully adopt and incorporate artificial intelligence (AI). In order to accomplish this, a range of adoption theories and models, such as the 'Unified Theory of Acceptance and Use of Technology' (UTAUT) model, have been utilised. The study formulates assumptions and constructs a conceptual model, which is subsequently verified using a survey of 329 participants. The results suggest that the suggested model can be a beneficial instrument for authorities to promote the effective implementation of AI in higher education.

Keywords: *Artificial Intelligence (AI,) Higher Education, Governance ,Adoption Theories, Unified Theory of Acceptance and Use of Technology (UTAUT)*

INTRODUCTION
Over the last two decades, the landscape of higher education in India has witnessed significant growth, as reported by The Times of India in 2018. Some experts attribute this development to measures initiated by the private sector. However, others contend that these initiatives are exploitative, poorly executed, and substandard, contributing to a decline in the overall quality of higher education in India. The erosion of institutional autonomy, inflexible educational structures, unwise affiliating systems, slow disposal processes, and insufficient financing from both public and private sectors are identified as the root causes of the deteriorating standards in Indian higher education. Consequently, there is an urgent need for a paradigm shift in the teaching-learning scenario and administrative activities involved in imparting higher education

in India. Various facets of higher education must be refreshed to ensure a good quality of education, with special attention focused on basic parameters for quality assurance.

Researchers emphasize the pressing need for the implementation of the latest technology, such as Artificial Intelligence (AI), in Indian higher education. AI has the potential to customize learning experiences to cater to the specific needs of all categories of students, offering a unique and tailored educational approach for each individual. AI-powered libraries can enhance the learning experience in higher educational institutes. Despite the potential benefits, the current state of AI technology may require further development to fully support such personalized learning experiences. Chatbots, powered by AI, can play a crucial role in providing personalized assistance for problem-solving and addressing individual students' needs, even outside regular class hours. These AI-enabled chatbots can offer solutions to admission queries, assist in administrative decision-making, and contribute to various aspects of student support. AI technology may also prove useful in creating 'smart content', such as digitized guides for textbooks and customizable digital learning interfaces at all levels of education. The integration of AI in higher education holds promise for addressing the increasing workload resulting from the massification of students. However, for AI to realize its benefits, it is essential for students, teaching and non-teaching staff, including administrative personnel (stakeholders), to embrace and adopt AI technologies. Despite this imperative, there is a scarcity of explicit studies on the adoption of AI in higher education within the Indian context.

In light of this scenario, this study aims to identify the factors influencing the adoption of AI in higher education. The following research questions will be addressed in this context:

1. How will the applications of AI impact the higher educational system in India?
2. What are the antecedents influencing the attitude of stakeholders in higher educational institutes in India towards the adoption of AI?
3. Can the behavioral intention of stakeholders in higher educational institutes in India influence the adoption of AI?

REVIEW OF EXISTING LITERATURE

The exploration of AI's impact on higher education in India reveals a transformative landscape with both opportunities and challenges. The integration of AI has the potential to significantly enhance governance, rendering it more effective and efficient. In the specific context of AI applications in Indian higher education, AI is conceptualized as computational systems capable of human-like processes, including adaptation, learning, synthesis, correction, and the utilization of diverse data for processing complex tasks. The anticipated benefits extend to students, teachers, administrative staff, and researchers, underscoring the imperative to embrace AI in higher education. Encouraging stakeholders to adopt this modern technology is seen as pivotal for the overall development of the higher education system in India.

The global pursuit of elevating the quality of education motivates governments in developed and developing countries to leverage modern technologies like AI. The application of AI is expected to modernize student assessment systems, offering insights into individual capabilities and fostering a more informed learning experience. Increasing investments by governments worldwide underscore the commitment to expanding higher education through the incorporation of modern technologies, particularly AI, to enhance educational quality.

Empirical studies consistently suggest that learning with AI outperforms traditional teacher-centric settings, and India is actively joining the global momentum in integrating AI into higher education.

As the adoption of AI gains traction, a critical question arises: how can potential users' acceptance attitudes be aligned with this technological shift? Recognizing that user acceptance of modern technology is a prominent research area in contemporary Information Technology Literature, various theories and models from Information System, Sociology, and Psychology attempt to explain users' intentions to adopt innovative technology like AI. Among these, the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al. emerges as particularly robust, explaining a substantial proportion of the variance in behavioral intention compared to other models and theories.

2 Formulation of Hypotheses and Conceptual Model

Drawing on the insights gained from the literature review, it becomes evident that the UTAUT model possesses superior explanatory power under identical data. The model comprises four exogenous factors—Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence. However, given that stakeholders in the present context are individuals associated with higher education, such as staff, teachers, students, and researchers, and are not likely to be significantly influenced by societal impacts, the construct of Social Influence is omitted from consideration. The decision to focus on the UTAUT model is reinforced by its incorporation of eight existing models, making it a comprehensive framework for synthesizing the acceptance attitudes and behaviors of stakeholders towards adopting AI.

Furthermore, attitude emerges as a crucial factor in interpreting users' intentions for technology acceptance. To capture this, Attitude is introduced as a mediating factor between Performance Expectancy and Behavioral Intention, Effort Expectancy and Behavioral Intention, and Effort Expectancy and Behavioral Intention, aligning with findings in several studies. Additionally, a new construct, 'Perceived Risk,' is introduced as an important exogenous variable, reflecting its relevance in other studies. Facilitating Conditions are proposed to have a direct linkage with Behavioral Intention, as supported by other studies. Thus, it is theorized that Perceived Risk, Performance Expectancy, and Effort Expectancy impact Behavioral Intention through the mediating role of Attitude, while Facilitating Conditions directly influence Behavioral Intention, ultimately influencing the adoption of AI in Higher Education.

In this conceptual framework, the UTAUT model is employed without considering moderators such as age, gender, experience, and voluntariness. The omission of these moderators is justified by the expectation that the attitudes of literate stakeholders in higher education would not be significantly influenced by these factors. The chosen constructs—Perceived Risk, Performance Expectancy, Effort Expectancy, Facilitating Condition, Attitude, and Behavioral Intention—are believed to comprehensively capture the dynamics of Adoption of AI in Higher Education. The subsequent section will delve into the elaboration of these constructs and the development of hypotheses within this framework.

Perceived risk (PR)

Perceived Risk (PR) is commonly understood as the belief that users may face losses when seeking a particular outcome. Since AI operates on the internet, Perceived Risk (PR) is a combination of behavioral and environmental insecurities. The unfriendly nature of internet functions contributes to behavioral insecurity, while the unpredictable nature of the internet adds to environmental insecurity. Studies indicate that a reduction in PR significantly influences users' attitudes. The theoretical model related to e-commerce suggests that PR negatively but significantly influences users' attitudes. Therefore, perceived risks are associated with users' negative feelings towards AI in higher education. In light of these discussions, the following hypothesis is posited: Perceived Risk (PR) has a negative and significant impact on users' Attitude (ATT) towards the Adoption of AI in Higher Education.

Performance expectancy (PE)

Performance Expectancy (PE) is the extent to which a user believes that using a new system would lead to considerable gains in job performance. Performance Expectancy is synonymous with perceived usefulness, outcome expectancy, and relative advantage. These beliefs have been employed in previous adoption theories. Perceived usefulness or relative advantage is similar to Performance Expectancy (PE) and has a significant and positive impact on Attitude (ATT). With these considerations, the following hypothesis is formulated: Performance Expectancy (PE) has a positive and significant impact on users' Attitude (ATT) in adopting AI in Higher Education.

Effort expectancy (EE)

Effort Expectancy (EE) is defined as the simplicity with which a user can use a new system. Perceived ease of use and Complexity, found in other models, convey the same concept as EE. The theoretical basis of other models reveals that perceived ease of use (similar to EE) is a significant and effective predictor of Attitude (ATT) in technology adoption research. This relationship is consistently supported in other studies. With these discussions, the following hypothesis is presented: Effort Expectancy (EE) has a significant and positive influence on Attitude (ATT) towards the Adoption of AI in Higher Education.

Facilitating conditions (FC)

Facilitating Conditions (FC) are defined as the extent to which an individual believes that conducive technical and allied infrastructure are effectively available to support the usage of the new system. FC encompasses the sense of behavioral control and compatibility with other models. A direct connection has been established between FC and Behavioral Intention (BI). Empirical studies demonstrate a significant influence of FC on BI in technology adoption by individuals. In the use of e-filing by US taxpayers, FC was meaningfully significant in interpreting the BI of taxpayers. With these considerations, the following hypotheses are provided: Facilitating Conditions (FC) have a positive and significant impact on Behavioral Intention (BI) of users in adopting AI in Higher Education. Additionally, it is proposed that FC has a positive and significant impact on Effort Expectancy (EE). This has been supported in other studies. Analyzing the factors influencing customers in using the e-services of Indonesian Airlines revealed that FC positively influences Effort Expectancy (EE). It is believed that providing a high-quality technical infrastructure or offering initial training to users in adopting new technology, falling under FC, may help users comprehend the system clearly. From this standpoint, the following hypothesis is posited: Facilitating Conditions (FC) have a positive and significant impact on Effort Expectancy (EE).

Attitude (ATT)

To perform a target behavior, individuals exhibit positive or negative feelings. This concept is encompassed by the sense of Attitude (Fishbein and Ajzen 1975). Davis et al. (1989) in the Technology Acceptance Model (TAM) postulate that Behavioral Intention (BI) is assessed by the Attitude of an individual towards using a system. Studies indicate that Attitude (ATT) influences the Behavioral Intention (BI) of users, as found in the Theory of Planned Behavior (TPB). Attitude (ATT) acts as a strong mediating variable in interpreting Behavioral Intention (BI), as evidenced in many other studies. Supported by this analysis and various research studies, the following hypothesis is derived: Attitude (ATT) of individuals in adopting AI in Higher Education positively and significantly impacts Behavioral Intention (BI) of users.

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

Behavioral Intention (BI) is associated with assessing the strength of an individual's intention to perform a specific behavior. This Behavioral Intention (BI) is an effective predictor of performing actual activities expressing that intention. BI serves as a mediating variable effectively influencing the performance of the behavior in favor of the activity to which one's intention is expressed. From this important standpoint, the following hypothesis is formulated: Behavioral Intention (BI) of users to adopt AI in Higher Education positively and significantly impacts the Adoption of AI in Higher Education (AAHE). After thorough discussions regarding the development of the model and explaining the mechanisms of developing the hypotheses, the conceptual model is shown. The hypotheses formulated are conceptually tested, and the model developed is validated through an appropriate methodology.

RESEARCH METHODOLOGY

To validate the conceptual model and test the hypotheses, we employed Partial Least Squares (PLS) regression analysis, which necessitates survey work. To facilitate this, we meticulously developed questionnaires using a step-by-step scale development approach, guided by an architectural framework and the insights of domain experts. This iterative process led to the creation of 33 statements framed as questions, primarily addressing various facets of AI technology within the higher education sector. These questions delved into topics such as the customization of educational content, the use of AI-powered chatbot technology to address individual student queries beyond the classroom, the ease of using AI technology, perceived risks associated with its use in higher education (e.g., answering student queries, handling admission procedures), and more.

Table 1 Demographic Profile of Respondents

Participants	Number	Percentage (%)
Students	205	62.31
Teachers	80	24.32
Administrative Staff	44	13.37

The study focused on higher education institutions in Delhi, Kolkata, Mumbai, and Bengaluru, engaging with students, faculty, and administrative staff. Within a 60-day timeframe, questionnaires were distributed to 359 respondents, and experts identified 30 responses as vague and biased. Feedback was assessed using a 5-point Likert scale.

Table 2 Estimation of Cronbach's α, VIF and AV (Discriminant Validity Test)

	PR	PE	EE	FC	ATT	BI	AAHE	AVE	α	VIF	Item No.
PR	**0.893**							0.797	0.892	3.7	4
PE	0.534	**0.908**						0.825	0.901	3.9	5
EE	0.501	0.544	**0.911**					0.830	0.876	4.1	5
FC	0.533	0.561	0.556	**0.912**				0.832	0.912	4.0	5
ATT	0.511	0.517	0.533	0.493	**0.917**			0.841	0.896	4.4	5
BI	0.504	0.511	0.499	0.506	0.537	**0.924**		0.854	0.910	4.4	5
AAHE	0.590	0.562	0.501	0.561	0.546	0.504	**0.909**	0.826	0.887	4.9	4

To assess questionnaire reliability, Loading Factors (LF), Average Variance Extracted (AVE), Composite Reliability (CR), and Maximum Shared Variance (MSV) were calculated. The established minimum values for LF, AVE, and CR are 0.707, 0.5, and 0.7, respectively. Cronbach's alpha values for each construct were below 0.6, affirming the reliability and consistency of the constructs.

Further tests for construct reliability, multicollinearity, and discriminant validity were conducted. The internal consistency of constructs was supported by Cronbach's alpha values below 0.6. To identify multicollinearity issues, the study examined whether the inner meanings of constructs were overly similar. PLS regression analysis, assessing the conceptual model's validity, was performed, and Variance Inflation Factor (VIF) values within the range of 3.3 to 5 were considered acceptable.

Table 3 Model Fit Summery Relating to the Research Model

Fit Index	Recommended value	Value in the model
Chi-Square ($\chi 2$)/Degree of Freedom (*df*)	≤ 3.000 (Kline 2005)	2.016
Goodness of Fit Index (GFI)	≥ 0.900 (Hoyle 1995)	0.907
Adjusted Goodness of Fit Index (AGFI)	≥ 0.800 (Segars and Grover 1993)	0.842
Comparative Fit Index (CFI)	≥ 0.930 (Hair et al. 2006)	0.957
Tucker Lewis index (TLI)	≥ 0.950 (Sharma et al. 2005)	0.962
Root Mean Square Error (RMSE)	≤ 0.070 (Steiger 2007)	0.024

Discriminant validity tests were conducted to ensure that each item had a strong relationship with its respective construct and a weak relationship with other constructs. Average Variance (AV) values were calculated, and the discriminant validity test was established if AV exceeded the correlation coefficients of that construct with other constructs. VIF values between 3.5 and 5 indicated the adequacy of the data.

Structural Equation Modeling (SEM) was employed to evaluate the relationships among latent variables and confirm the model's fit. Parameters fell within standard acceptable limits, affirming the model's adequacy. The structural model was presented with path weights, significance levels, and estimated R2 values, providing insight into the explanatory power of the model.

STUDY RESULTS

The findings reveal the outcomes related to seven hypotheses (H1, H2, H3, H4a, H4b, H5, and H6). Analysis suggests an insignificant effect of Performance Expectancy (PE) on the users' Attitude (ATT) toward AI adoption in higher education. The associated path coefficient is as low as 0.021, with a significance level ($p > 0.05$), leading to the non-support of Hypothesis H2. It is observed that Effort Expectancy (EE) can be explained by Facilitating Conditions (FC) to the extent of 74%. Perceived Risk (PR) exerts a negative impact on ATT, with a path coefficient of -0.206 and a high significance level ($p < 0.001$). The three exogenous variables—PR, PE, and EE— collectively explain ATT to the extent of 56%. Conversely, ATT and FC jointly explain Behavioral Intention (BI) to the extent of 70%. The mediating variable BI can elucidate the target Adoption of AI in Higher Education (AAHE) to the extent of 84%. The model's explanatory power is 84%, with ATT exhibiting a greater influence on BI compared to FC, as evidenced by their respective path coefficients of 0.739 and 0.229. The model's effectiveness is evident, given its relatively appreciable explanatory power of 84%.

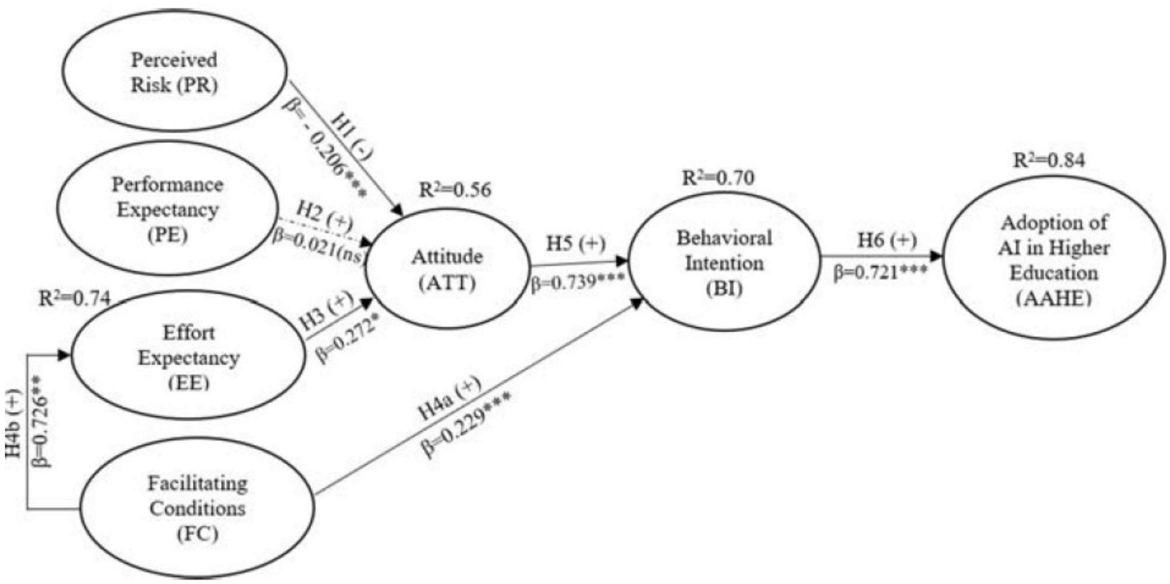

Fig. 2: Structural Model with Path Weights and Significance Level ns $p > 0.05$; *$p < 0.05$; **$p < 0.01$;***$p < 0.001$

KEY FINDINGS

The results underscore several key findings:

- Perceived Risk (PR) and Effort Expectancy (EE) significantly impact (negatively for PR and positively for EE) the Attitude (ATT) of stakeholders in higher education institutes regarding the adoption of AI.

- Performance Expectancy (PE) does not have a significant impact on the Attitude (ATT) of stakeholders in higher education institutes regarding the adoption of AI.

- Facilitating Conditions (FC) have a significant and positive impact on both Effort Expectancy (EE) and Attitude (ATT) of stakeholders in higher education institutes for the adoption of AI.
- Behavioral Intention (BI) has a significant and positive impact on the adoption of AI in higher education.

The model, being straightforward, provides valuable insights for authorities aiming to implement AI adoption, thereby enhancing the overall performance of higher educational institutes in India.

Table 4 Path Weights with Estimation of R^2

Effect	Hypothesis	Path	Sign	β-value	Significance Level	R^2	Remarks
Effect on ATT						0.56	
By PR	H1	PR → ATT	–	0.206	***(p < 0.001)		Supported
By PE	H2	PE → ATT	+	0.021	ns		Not Supported
By EE	H3	EE → ATT	+	0.272	*(p < 0.05)		Supported
Effect on EE						0.74	
By FC	H4b	FC → EE	+	0.726	**(p < 0.01)		Supported
Effect on BI						0.70	
By FC	H4a	FC → BI	+	0.229	***(p < 0.001)		Supported
By ATT	H5	ATT → BI	+	0.739	***(p < 0.001)		Supported
Effect on AAHE						0.84	
By BI	H6	BI→AAHE	+	0.721	***(p < 0.001)		Supported

Limitations and Future Research Directions

While this study has presented a model with high explanatory power, it is crucial to acknowledge specific limitations. In the context of India, the utilization of AI in higher education is still in its infancy, with no confirmed adopters identified to date. Therefore, all synthesized findings remain predictive. The survey collected 329 usable responses exclusively from non-adopters of AI in higher education, limiting the generalizability of the results. Caution is advised when extending these findings to adopters, and further research should aim to include actual adopters, potentially introducing an additional construct such as "actual use" for model extension and validation.

Furthermore, there is room for exploring additional boundary conditions affecting AI adoption in higher education, such as 'image' and 'output expectancy.' While these factors were not initially considered, the model's explanatory power reached a high of 84%. Future research could revalidate the model after incorporating these factors to assess potential enhancements in explanatory power.

The study's reliance on 329 inputs may not fully represent the broader landscape of the Indian higher education system. Future research should consider longitudinal investigations with extended timeframes and data collection to offer a more comprehensive and generic model.

Although the UTAUT model served as a foundation for this study, the exclusion of its four moderators was a deliberate choice, assuming their limited impact on literate stakeholders.

While this decision did not compromise the theoretical model's outcome, future researchers may explore the inclusion of these moderators to gauge any potential improvement in results. The model's explanatory power of 84% might attract criticism, suggesting that incorporating additional boundary conditions could have further enriched its explanatory capabilities. This aspect remains open for future researchers to explore, aiming for a theoretical model with complete explanatory power.

Theoretical Implications

In adopting the UTAUT model, this study recognized its emphasis on four constructs: Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI). However, PE and EE primarily address technological context, while FC and SI focus on implementation context. In this study, where students, teachers, and administrative staff constitute the principal stakeholders in AI adoption for higher education, considering factors affecting the individual context becomes imperative. Consequently, Attitude (ATT) was introduced as a mediating variable, aligning with prior research. The proposed theoretical model outperformed by achieving an explanatory power of 84%, potentially due to the inclusion of more suitable constructs for explicating stakeholders' adoption behavior. This model did not simply replicate the UTAUT model; it represents a unique theoretical contribution, especially in the context of AI adoption in Indian higher education, where explicit research is still lacking.

The incorporation of Perceived Risk (PR) as an exogenous variable is a distinctive feature of this proposed theoretical model. While trust in the adoption of AI is considered crucial, PR was included based on research equating trust with stakeholders' behaviors involving risk-taking. This represents a noteworthy addition to the proposed theoretical model.

Furthermore, the effect of Facilitating Conditions (FC) on Effort Expectancy (EE) (H4b) was not considered in the UTAUT model or its extensions. This signifies that the availability of knowledge, infrastructure, and system opportunities, collectively framed as FC, makes AI usage more accessible for stakeholders. The potential for increased adoption is thus heightened. FC alone was able to explain EE to the extent of 74%, indicating that this consideration has significantly enriched the explanation of AI adoption in higher education by stakeholders, constituting a substantial contribution of this theoretical model.

The decision to exclude Social Influence (SI), an exogenous variable in UTAUT, reflects the recognition that stakeholders' decision to adopt AI in their higher studies or administrative tasks may not be significantly influenced by societal factors. This deliberate omission contributes to the unique focus of this theoretical model. The inclusion of ATT and BI as endogenous variables is credited with enhancing the model's performance, as evidenced by its high explanatory power of 84%. The decision not to consider moderators in the theoretical model, while included in UTAUT, is justified by the belief that these moderators may not significantly affect literate stakeholders in this particular context. This unique aspect is considered a distinctive contribution to the proposed theoretical model.

Practical and Policy Implications

The study's findings underscore the pivotal role of Attitude in achieving the goals outlined. This factor serves as a crucial mediator, exerting a significant impact on the Behavioral Intention of individuals to adopt AI in higher education in India. Authorities of higher education institutes are encouraged to shape stakeholders' attitudes as a means of influencing their intentions and behaviors positively. Notably, Performance Expectancy (PE) and Effort Expectancy (EE) emerge as antecedents of Attitude (ATT) (H2 and H3), signaling the importance placed on technological considerations. Assessing the utility (PE) and ease of use (EE) of the AI system becomes crucial, necessitating a concerted effort by designers, developers, and system managers to align the system with user needs, minimize complexity, and raise user awareness regarding the system's capabilities. Strategic communication through product brochures, success stories, and live demonstrations can contribute to enhancing user understanding and acceptance.

The observed negative impact of Perceived Risk (PR) on Attitude (H1) underscores the need for higher education authorities and the Government of India's Human Resource Development Department to promote privacy and security measures. Transparent communication of measures addressing security and privacy challenges is essential, fostering stakeholder awareness and safeguarding against cyber frauds and security infringements. Stakeholders should receive training on cybersecurity issues, and appropriate policies should be formulated to penalize offenders, thereby enhancing user confidence in AI adoption in higher education.

Conclusion

AI solutions offer vast opportunities for teaching, learning, and administrative functions in Indian higher education. However, the conceptualization of AI use is still in its nascent stages. This study explores the potential for AI adoption in higher education, providing a model that identifies determinants facilitating adoption. It asserts that higher education institutes stand to gain effective advantages by employing AI, fostering accurate and rapid knowledge exchange that can enhance the intellectual health of higher education when strategically applied in practice.

It is crucial to emphasize that education remains fundamentally a human-centric endeavor, not solely dependent on technological solutions. While AI may provide cutting-edge advancements, human identification of problems, critique, and the nurturing of creativity remain integral. AI applications should complement human efforts, aligning with the needs of higher education in India for successful outcomes. This study primarily focuses on the adoption issues of AI in higher education, hypothesizing that Performance Expectancy would significantly impact Attitude. However, post-validation statistical analysis revealed an insignificant impact of PE on ATT (H2), suggesting that stakeholders in India have not fully adopted AI technology, lacking opportunities to test its performance-enhancing capabilities.

As India moves towards complete AI adoption in higher education, it is expected that Performance Expectancy will positively and significantly impact stakeholder attitudes, influencing

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