

AI Awareness, Facilitating Factors, Perceived Risk, Attitude Toward AI, Behavior Toward AI, AI Application and Ethical Concerns: A Study of Higher Education Institutions

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Abstract: AI is one of the most significant trends in the modern world, and it changes industries and redesigns people's lives and occupations. This research aims to establish attitudes and behavior toward AI using 439 finalized samples of instructors in academic institutions in Multan, Pakistan. Key variables like AI awareness level, facilitating factors, perceived risk, and ethical concerns were tested for the application of AI. The results show that AI awareness, the facilitating factors, and perceived risks impact attitudes towards AI. A positive attitude predicts AI-related behavior, which is a key determinant of AI application in educational institutions. However, ethical concern plays a non-significant role in the relationship between behavior and AI application, suggesting that it may not have a direct influence on the adoption of AI from this perspective. This paper highlights the necessity of an awareness campaign and the establishment of conducive conditions for AI use. Some of the limitations include the cross-sectional study design and the geographical location of the participants, which may affect the generalization of the findings. Future research will need to include longitudinal designs, different populations, and other social psychological factors like trust, emotions, and norms to investigate AI adoption patterns further.

Keywords: Artificial Intelligence, AI Adoption, AI Awareness, Facilitating Factors, Perceived Risk, Attitude Toward AI, Behavior Toward AI, AI Application, Ethical Concerns

Introduction

Artificial Intelligence has grown to be the most transformative force within contemporary society, affecting areas ranging from social life and health to financial services. Artificial intelligence drives immense change throughout industries, basically reshaping the way one would go about living and working. Higher education, in this regard, will be highly affected as most universities and learning institutions continue to incorporate AI in teaching methods, administrative roles, and research work to enhance such areas (Hwang et al., 2020). As technology in the teaching-learning process progresses, many more courses and even full degrees can be completed through online study (Dieguez et al., 2021). It makes it easier for students to gain a chance to study at the university level and increases the versatility of the learning system. Due to the changes in the learning environment and students' access to technology, children in education are learning from different environments, thus emphasizing cross-cultural interactions and global responsibility. Furthermore, given the fast-growing rate in the modern world through technological enhancements, universities assume the task of innovators and research centres (Yoosomboon et al., 2021).

AI technologies have transformed higher education through personalized learning, informed decisions based on data analysis, and innovative teaching-learning methodology. Examples are found in the works of (Oliveira et al., 2019; Grimus, 2020). As far as enablers are concerned, the major ones that actually help in smooth integration are the availability of technical infrastructure, training programs, and institutional policies. For example, resource provisions for enhancing adaptive learning systems make them more adopted in learning institutions, whereas perceived risks such as privacy issues, concerns over bias nature of algorithms used, and ethical issues reduce this level of adoption. In order to establish trust, there must be clarity in relation to practices and sound governance frameworks developed. Similarly, Sallam et al.

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(2024) observed that institutions have to pay attention to ethical concerns, such as the misuse of AI in assessment and make appropriate rules to capture the hearts of stakeholders. The perception towards AI determines the decision-making process within higher learning institutions. Social attitudes from experience of the effectiveness of AI will be positive and will engage people to adopt the technology, while negative attitudes will slow the adoption process (Saihi et al., 2024)

Positive attitudes toward AI are developed when the users see the potential value of AI in improving learning performance. Rahiman and Kodikal (2024) found that when the teaching faculty sees enhanced efficacy of rapid and individualized learning, which is enabled by AI tools, they turn into champions from critics. Such a transformation encourages the calls for pilot projects where most of the benefits are demonstrable on paper to stakeholders. These attitudes manifest towards AI as a practice regarding AI in teaching and learning, which includes adopting AI technology in the curriculum or declining to do so (Maheshwari, 2024). The variety of applications of AI systems, ranging from AI-assisted teaching-learning environments to administrative innovations, reveal how far AI can go in enhancing higher learning institutions. But the problem lies in implementation; the aforementioned challenges must be solved to support equity and ethical use (Rana et al., 2024). This means that awareness about AI technologies equally plays a major role and is closely related to the adoption of these technologies. Those organizations that continually spread information regarding AI possibilities contribute to the development of a culture of innovation. For example, Wang et al. (2024) pointed out that successful AI promoter of AI literacy for students and faculty creates awareness and understanding of AI, which assists stakeholders in making the right decisions concerning AI. The authors stressed that increasing awareness reduces misperceptions and strengthens confidence in AI systems, which was the main focus of their study.

Literature Review

AI Awareness has a Significant Relationship with Attitude Toward AI

This is a topic that has been of research interest in the recent past as people have become more conscious of AI and have different mindsets towards adopting it in different areas. Research has also shown that the amount of enacted experience you have with AI correlates positively with your attitudes towards AI and your intent to work with AI in your practice. Education in the area of Artificial Intelligence (AI) is crucial for students to effectively solve societal and technological problems. This study by Chai et al. (2021) developed and validated a survey measuring primary school students' behavioural intention to learn AI across five factors: self-efficacy, readiness for AI usage, knowledgeable attitudes about the social effects of AI, AI knowledge, and AI usage behaviour intention. The results show that all the factors have a direct impact on students' motivation to learn AI, which can be informative for the dissemination of AI education. This study by Scantamburlo et al. (2024) concluded that AI literacy, ethical regulation, and education are key factors favouring a trustworthy AI environment and provided suggestions for its regulation in Europe.

Minkevics and Kampars (2021) aims to analyze the factors enhancing the use of AI with the moderating variable of perceived technology attitudes among Bangladeshi professionals. It reviews factors like performance expectancy and effort expectancy, social norms, facilitating conditions, perceived usefulness, perceived ease of use, and behavioral intention toward the use of AI. The study also reveals that performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived usefulness all contribute to the usage of AI. Hence it can be hypothesized that

H1: *AI awareness has a significant relationship with Attitude toward AI*

Facilitating Factors have a Significant Relationship with Attitude toward AI

Previous work has explored the connection between facilitating factors and attitudes toward artificial intelligence (AI). These factors include facilitating conditions, performance expectancy, social influence and effort expectancy, and where all have been discovered to have a strong influence on individuals' attitude towards AI. For example, an analysis of AI adoption found that perceived usefulness and effort expectancy were strong indicators of behavioral intention towards AI with attitudes influencing these relationships (Kelly et al., 2023). In addition, based on previous research, social influence and facilitating

factor is found to be relevant in the process of using AI, and it was postulated that speak positively towards AI (O'Shaughnessy et al., 2023). Among SDs in India, facilitating condition which refers to the sufficient and appropriate support and resources to use AI-enabled tools has been found to be influential in the use of the technology. It shows that these conditions actively influence the behavioral usage of AI and they encourage positive attitudes towards AI, which in turn increases adoption levels (Jain et al., 2022).

Further, Gerlich (2023) conducted a multi-dimensional study on AI perceptions and acceptance that reveals that the facilitating factors including user experience or cost aspect and AI acceptance are positively correlated. The study also brings to the fore the significance of facilitating conditions – technical and organizational – in shaping the attitudes towards AI, which, in return, determine the behavior and intentions of the individuals to utilize AI technologies. Moreover, studies which adopted the amalgamation of different perceptual theoretical models of technology acceptance reveal that the facilitating condition which encompasses elements such as the technical support and organizational backing are central determinants on how individuals perceive the AI. These conditions influence perceived ease of use are key aspects to positive attitude and adoption of AI systems (Koenig, 2024). Hence it can be hypothesized that

H2: *Facilitating Factors have a significant relationship with Attitude toward AI*

Perceived Risk has a significant relationship with Attitude toward AI

Subsequent research has expanded on the link between perceived risk and views on artificial intelligence (AI). For example, the study on artificial intelligence risk perception reveals that people's intentions to adopt artificial intelligence are a function of their perception of the risks and benefits of the technology. This gives a clear sign that perceived risks should be responded to promote a greater positive attitude toward AI (Schwesig et al., 2023). Further, research has revealed that in high-impact situations, the decisions made by AI are perceived to be less risky and this implies that the perception and attitude of people towards AI can be determined by the perspective under which AI is used (Klein et al., 2024). Hwang et al. (2024) studied behavioral and switching intentions of South Korean and US consumers toward AI-based facial recognition payment technology in restaurants. Attitude and subjective norms surfaced as strong predictors of intentions to switch to and use facial recognition payment for both groups. Perception about this technology is also influenced by the psychological risk level since cultural differences can also mediate this particular relationship. In conclusion, this research indicates that perceived risk is influential when it comes to the attitude toward AI as well as the identification of perceived risks can be important for increasing the acceptance and use of AI. Hence it can be hypothesized that

H3: *Perceived Risk has a significant relationship with Attitude toward AI*

Attitude toward AI has a Significant Relationship with Behavior toward AI

In recent years, several researchers have taken an interest in the correlation between perception and behavior about AI, which shows substantial links between them. Li and Zheng (2024) examined the relationship of social media engagement with perceptions toward AI solutions with the moderating effects of perceived AI equity and risk. Their study found that social media use was associated with more positive attitudes toward AI, mediated by higher perceived AI fairness and lower perceived AI threat, indicating that technology attitudes are a function of information exposure that can affect technology behavior. Hajam and Gahir (2024) surveyed and found out that university students had positive attitudes towards AI, with science students being more positive THAN arts and commerce students. This implies that the educational background somehow plays a major role in the perception of AI which in turn may have an impact on the kind of engagement that an individual could have towards AI technologies. Méndez-Suárez et al. (2024) explored the determinants of attitudes towards AI consumers and identified the opinion about S&T mainly as a robust determinant of the attitudes towards AI. It was observed that participants who had a favorable attitude towards S&T also had a favorable attitude towards AI and vice versa. Such findings indicate that general perceptions towards technology can determine general perceptions and behavior toward AI. Hence it can be hypothesized that

H4: *Attitude toward AI has a significant relationship with Behavior toward AI*

Behavior toward AI has a Significant Relationship with AI Application

Li et al. (2022) explored medical students’ knowledge and attitudes about the use of AI in learning clinical practice. The research revealed an association between personal relevance, subjective norm, and perceived behavioral control over a given behavior and the actual behavior intention to learn, which was positively correlated to actual learning. The study provides insights into how healthcare education can enhance the teaching of medical Artificial Intelligence. Kaya et al. (2024) reported mostly positive responses to attitudes about AI. In assessing the attitudes, the following dimensions were used; cognitive behavioral and emotional attitudes were used and, in this case, the emotional attitudes were stronger. The use and safety perceptions of these attitudes may further determine AI use in the future; therefore, the researchers advocated for more education of AI to improve students’ attitudes. According to Katsantonis and Katsantonis (2024) survey of university social sciences students regarding AI, the overall response was positive. The attitude was distinguished in terms of the cognitive, behavioral, and emotional components that were analyzed; the emotional component being more significant. These attitudes point to the perception on the use of Future AI & safety which dictates the impact of more education to improve students’ favorable attitudes and future use of AI. Hence it can be hypothesized that

H5: Behavior toward AI has a significant relationship with AI Application

Ethical Concerns Moderate the Relationship between Behavior toward AI and AI Application

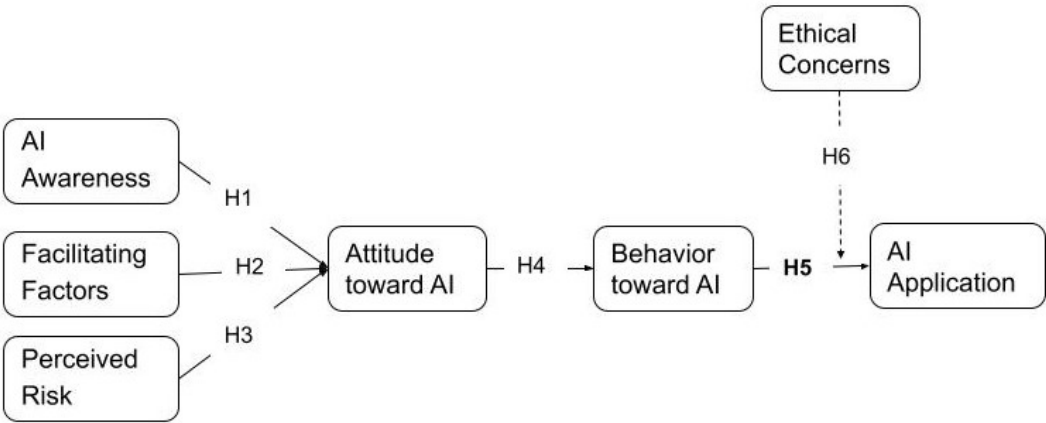
The interplay between ethical concerns and the behavioral adoption or resistance to AI technologies is a critical area of scholarly exploration. This relationship significantly affects how AI applications are designed, perceived, and integrated across various sectors. Ethical concerns act as a moderating factor, influencing both the trustworthiness of AI and its acceptance by users. Oprea and Bâra (2024) concluded that collaboration between technology makers and policymakers to ensure ethical, widely accepted advancements aligned with societal values. Shum and Lau (2024) conducted a latent profile analysis on attitudes toward AI among older adults. Ethical considerations surrounding inclusivity and fairness were identified as key moderators of trust and behavior, particularly in AI-powered smartphone applications. Atalla et al. (2024) identified positive attitude, ethical awareness, and creativity as factors having a positive relationship with each other and showed that ethical awareness plays a mediating role in the relationship between positive attitude and innovative work behaviors. Thus, these outcomes speak about the importance of ethical sensitization to enhance positive perceptions about AI and consequently, the development of innovative nursing practices that can help nurses’ wellbeing. Ethical considerations are identified in the literature as having a significant moderating effect on the Attitudes and behaviors toward AI and related technologies. Hence it can be hypothesized that

H6: Ethical Concerns moderate the relationship between Behavior toward AI and AI Application

Research Framework

Figure 1

Conceptual Framework



Methodology and Data Collection

The study employed a quantitative research methodology, utilizing a cross-sectional survey design deemed most suitable for this type of research. A cohort of academic instructors from educational institutions was chosen via stratified random sampling and convenience sampling methods (Waris & Hameed, 2020; Alzghoul et al., 2024). The target population comprised academicians at various ranks, including associate professors, assistant professors, lecturers, and teaching assistants, instructing across multiple academic tiers, bachelor, master, and doctoral programs, in diverse departments such as Business Administration, Computer Sciences, and Social Sciences. The population was divided into strata and was then approached based on convenience sampling (Anwar et al., 2020). The academic instructors belonging to other cities were also contacted but no positive response was achieved. Also reaching out to them through personal visits would cost money and time, due to these factors the research was confined to Multan only. The research instrument comprised validated assessments of the variables, including AI Awareness, facilitating factors, perceived risk, and attitude toward AI, behavior toward AI, AI application, and ethical concerns pertinent to the current investigation (Murray, 1999). Data was gathered via a questionnaire distributed to 500 academic instructors working in private and public sector higher education institutions in Multan, Pakistan. SEM-PLS was used to assess the correlations among behavioral factors, AI Awareness, facilitating factors, perceived risk, attitude toward AI, behavior toward AI, and AI application, and evaluated the moderating influence of ethical concerns (Hair et al., 2019). The heterogeneity of the target group is essential since it provides thorough feedback (Mize & Manago, 2022). The study aims to identify variances in emotional and behavioral factors. The sample size was 139, still larger than ten times the number of reflective indicators, as suggested by (Chin & Newsted, 1999). Following the screening, the final sample size for this research comprised 439 valid replies. This sample size is selected based on practical considerations and statistical power calculations (Rahman et al., 2012). The researcher strives to establish a balance between an appropriate representation of the target population and the feasibility of data collection and analysis within the given resources and timeframe (Ahmed, 2024). By incorporating 439 instructors from diverse levels and departments, the sample size provides a sufficiently large dataset for undertaking significant statistical analysis (Hair et al., 2013). The table below summarizes the faculty members' statistics in various private and public higher education institutions of Multan.

Table 1
Faculty Member Statistics

Department	Associate Professor	Assistant Professor	Lecturer	Teaching Assistant	Total
Bahauddin Zakariya University Multan					
Computer Science	4	8	5	15	32
Business Administration	18	19	16	13	66
Social science	12	60	14	23	109
207					
Muhammad Nawaz Sharif University of Agriculture Multan					
Computer Science	2	2	7	15	26
Agri Business	2	1	4	19	26
Social science	0	4	4	6	14
66					
National University of Modern Languages Multan					
Computer Science	1	4	28	13	46
Business Administration	1	47	56	10	114
Social science	0	62	94	21	177
337					

EMERSON University Multan					
Computer Science	0	10	2	15	27
Business Administration	0	9	2	20	31
Social science	3	22	1	7	33
91					
University of Education Multan					
Computer Science	3	8	7	12	30
Business Administration	2	3	10	8	23
Social science	2	2	2	10	53
106					
NFC Multan					
Computer Science	0	3	9	12	24
Business Administration	0	4	5	8	17
41					
Institute of Southern Punjab Multan					
Computer Science	4	4	22	12	42
Business Administration	4	6	10	8	28
Social science	13	16	24	15	68
138					
National College of Business Administration & Economics Multan					
Computer Science	1	4	12	17	34
Business Administration	3	2	8	9	22
Social science	12	12	15	12	51
107					
Multan University of Science & Technology					
Computer Science	5	5	12	15	37
Business Administration	3	2	9	8	22
Social science	8	12	15	10	45
104					
University of Central Punjab Multan Campus					
Computer Science	3	8	15	16	42
Business Administration	3	4	6	12	25
Social science	9	12	15	8	44
111					
KAIMS College Multan					
Computer Science	1	7	12	12	32
Business Administration	2	3	10	5	20
Social science	5	11	13	18	47
99					
CITY College Multan					
Computer Science	0	0	10	5	15
Business Administration	0	0	10	8	18
Social science	0	0	14	2	16
49					
GRAND TOTAL	1365				

Measurement Instrument

In this study, measurement tools were selected from following recognized literature. Every item was stated positively (Rolstad et al., 2011). AI Awareness, facilitating factors, perceived risk, attitude toward AI, behavior toward AI, and AI application were adapted (Rahiman & Kodikal, 2024). The moderating element of ethical concern was measured using a scale adapted from (Fui-Hoon Nah et al., 2023). All the questions were evaluated using a five-point Likert scale, ranging from strongly disagree to strongly agree (Leung, 2011).

Table 2
Measurement Instrument

Variable/Construct	No of Items	Source
AI Awareness	4	(Rahiman & Kodikal, 2024)
Facilitating factors	6	(Rahiman & Kodikal, 2024)
Perceived Risk	4	(Rahiman & Kodikal, 2024)
Attitude toward AI	5	(Rahiman & Kodikal, 2024)
Behavior toward AI	5	(Rahiman & Kodikal, 2024)
AI Application	2	(Rahiman & Kodikal, 2024)
Ethical Concerns	5	(Fui-Hoon Nah et al., 2023)

Statistical Analyses

Response Rate

Based on the survey questions, we allow the respondent to voice their thoughts (Marshall, 2005). Consequently, people may easily link their experiences when answering the questionnaire (Murray, 1999). Through this strategy, we assemble accurate and correct data for our investigation, consequently validating the primary assumption of the study (Ansari et al., 2024). Of the 500 questionnaires distributed to the participants, 462 (92%) were returned and after screening, the finished sample consisted of 439 (88%).

Table 3
Response Rate

Description	Circulated	%
Total Disseminated Questionnaires	500	100%
Received Questionnaires	462	92%
Finalized Sample	439	88%

Demographic Profile of the Respondents

The demographic analysis reveals that out of the total 295 respondents, 61% are male and 39% are female. A major chunk, 46%, of the sample belongs to the 36-45 age bracket while 54% hold a master's degree and 46% are PhD degree holders. 45% of respondents were from the Department of Business Administration, 38% were from Computer Science and 17% were associated with Social Sciences Department. As far as their organizational ranks are concerned, 52% were lecturers, 22% were assistant professors, 18% were associate professors and 8% were teaching assistants. Table 2 summarizes the demographic profile in detail.

Table 4
Demographic Analysis

Characteristics	Percentage
Age of Respondents	
25-35	18%
36-45	46%
46-55	26%
55-and above	10%
Gender	
Male	61%
Female	39%

Characteristics	Percentage
Academic Qualification	
Masters	54%
PhD	46%
Department	
Business Administration	45%
Computer Sciences	38%
Social Sciences	17%
Organizational Rank	
Associate Professor	18%
Assistant Professor	22%
Lecturer	52%
Teacher Assistant	8%

Data Analysis

Structural Equation Modelling (SEM) is the preferred method for social science data analysis (J. F. Hair et al., 2019). The researchers in this study tested the suggested theories using Smart-PLS and PLS-SEM, which help researchers to study complex models with multiple constructs, a large number of mechanisms, ideas, and structural routes without assuming anything about the distribution of data, and a cause-and-effect SEM prediction strategy that highlights estimation in model assessment (Hair et al., 2013).

Results

Figure 2

Measurement Model

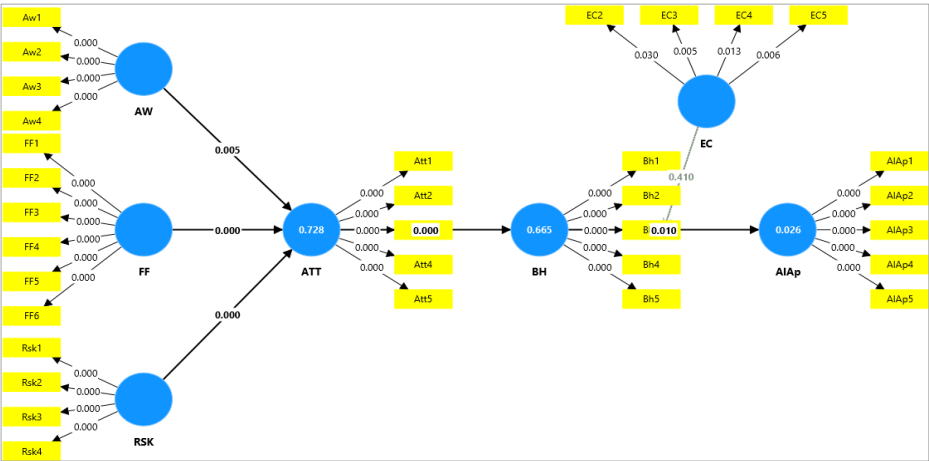
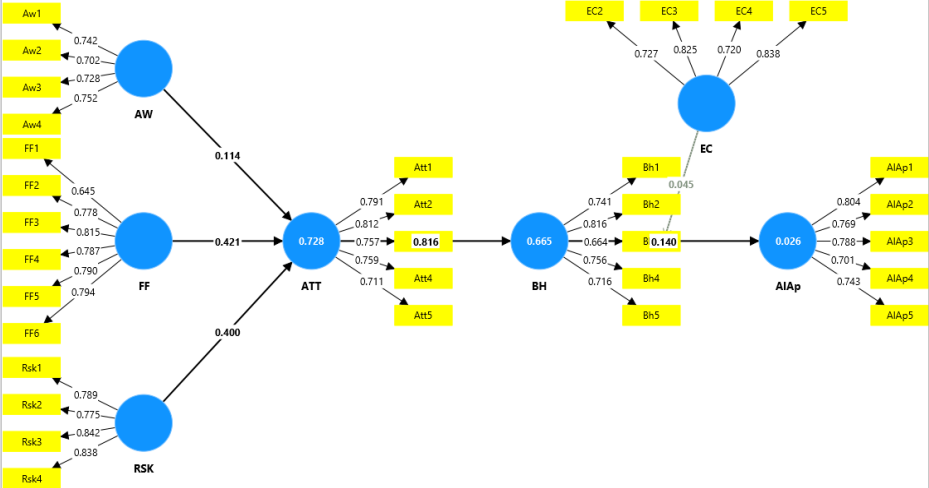


Figure 3

Structural Model



Measurement Model

The evaluation of the proposed model was conducted using two approaches: partial least squares structural equation modeling (PLS-SEM) (Ahmad & Hayee, 2024). The initial stage involved the assessment of the measurement model, which was subsequently followed by an analysis of the structural model (Hair et al., 2011). The evaluation of the MME focused on its internal consistency reliability, discriminant validity, and convergent validity (Hair et al., 2018).

Internal Consistency, Reliability, and Convergent Validity

The Average Variance Extracted (AVE) and Composite Reliability (CR) significantly exceeded the 0.50 threshold (Hermanto & Srimulyani, 2022). The model successfully met the specified Internal Consistency Reliability (ICR) and Convergent Validity (CV) criteria. All constructs showed consistency ratios (CR) above 0.7 and average values (AVE) greater than 0.50, as shown in Table 4. The constructs in Table 5 fulfilled the criteria required to be classified as dependent variables, following the Fornell and Larcker standard (Fornell & Larcker, 1981). The assessment of Convergent Validity (CV) was performed through factor loading, as described by (J. F. Hair et al., 2019). The data were collected from a single use, so there were chances of common method bias. *VIF* was used to address the issue of common method bias, table 7 indicates that *VIF* for all indicators is well below the threshold of 3 (Kock, 2017).

Table 6 shows that during the initial model evaluation, all component factor loadings were higher than the minimal threshold of 0.70 (S. Ahmad et al., 2016), except for only one item of the variable “ethical concerns”, which was removed before bootstrapping as it did not contribute to the measurement of the construct. To evaluate discriminant validity, (Henseler et al., 2015) proposed an innovative method called the Fornell and Larcker standard, which is best between 0 and 0.85 as indicated in Table 5.

Table 5
Measurement Model

Constructs	Cronbach's alpha	CR (rho_a)	CR (rho_c)	(AVE)
AIAp	0.822	0.840	0.873	0.581
ATT	0.824	0.825	0.877	0.588
AW	0.710	0.713	0.821	0.535
BH	0.792	0.797	0.858	0.548
EC	0.794	0.813	0.860	0.608
FF	0.861	0.867	0.897	0.593
RSK	0.828	0.834	0.885	0.659

Table 6
Discriminant validity (Fornell and Larcker Standard)

Constructs	AIAp	ATT	AW	BH	EC	FF	RSK
AIAp	0.762						
ATT	0.135	0.767					
AW	0.065	0.670	0.731				
BH	0.143	0.816	0.775	0.740			
EC	-0.057	0.010	0.022	0.019	0.780		
FF	0.113	0.802	0.732	0.840	-0.034	0.770	
RSK	0.144	0.784	0.620	0.725	-0.056	0.743	0.812

Table 7
Factor Loadings, and VIF

Item	FL	VIF
AIAp1	0.804	1.658
AIAp2	0.769	1.535
AIAp3	0.788	1.765
AIAp4	0.701	1.509
AIAp5	0.743	1.738
Att1	0.791	1.779
Att2	0.812	1.917
Att3	0.757	1.648
Att4	0.759	1.663
Att5	0.711	1.426
Aw1	0.742	1.400
Aw2	0.702	1.335
Aw3	0.728	1.384
Aw4	0.752	1.354
Bh1	0.741	1.887
Bh2	0.816	2.152
Bh3	0.664	1.336
Bh4	0.756	1.540
Bh5	0.716	1.451
EC2	0.727	2.451
EC3	0.825	1.544
EC4	0.720	1.339
EC5	0.838	2.731
FF1	0.645	1.414
FF2	0.778	1.841
FF3	0.815	2.130
FF4	0.787	2.082
FF5	0.790	1.983
FF6	0.794	2.007
Rsk1	0.789	1.560
Rsk2	0.775	1.742
Rsk3	0.842	2.036
Rsk4	0.838	1.863

The composite reliability, Cronbach's alpha, rho_A, average value retrieved, and other metrics for convergent validity all exceeded the cutoff values and were considered acceptable (J. F. Hair et al., 2019). Convergent validity values must surpass the specified criteria ($\text{rho_A} \geq 0.7$, $\text{CR} \geq 0.8$, $\text{AVE} \geq 0.50$, and $\text{CA} \geq 0.80$) (Ali et al., 2024). All variables demonstrated satisfactory convergent validity, falling within the acceptable range. To assess cross-loadings and discriminant validity, the Fornell-Larcker criterion was employed.

To ensure the absence of multicollinearity and common method bias, the variance inflation factor (VIF) values were carefully examined (Shahzad et al., 2024). All VIF values, ranging from 1.336 to 3.731, were

below the threshold of 5, indicating no evidence of multicollinearity and confirming that the model is free from common method bias contamination (Ansari et al., 2024).

Hypothesis Testing

Our confidence range was computed using the bias-corrected and accelerated (BCA) method to lessen the effect of bias. The bootstrapping method was used to test the hypotheses at a significance level of 0.05. The purpose of this calculation was to produce the t-statistics, p-values, and standard errors of the path coefficient to statistically compare the hypotheses. The findings of this study have directly contributed to the validation of hypotheses H1, H2, H3, H4, and H5. As per the first hypothesis (H1), there was a statistically significant influence of AW on ATT. The authors examined the findings in Table 7 ($\beta = 0.114$; $t = 2.786$; $p < 0.01$) to reinforce this theory, confirming the existing study (Minkevics & Kampars, 2021). These findings provide statistical evidence in favor of accepting hypothesis H1. The second hypothesis (H2) states that FF had a statistically significant impact on ATT. The authors reviewed the findings in Table 7 ($\beta = 0.421$; $t = 8.406$; $p < 0.01$) to corroborate this notion. These data give statistical evidence in support of accepting hypothesis H2, further strengthening the findings (Gerlich, 2023). According to the third hypothesis (H3), RSK significantly affected ATT. The findings in Table 7 ($\beta = 0.400$; $t = 9.949$; $p < 0.01$) were examined by the authors to support this idea. These data yield statistical evidence in support of accepting hypothesis H3, also confirmed by existing research (Schwesig et al., 2023). Based on the fourth hypothesis (H4), ATT substantially affected BH. The results presented in Table 7 ($\beta = 0.816$; $t = 42.718$; $p < 0.01$) have been investigated by the authors to corroborate this idea. These data yield empirical proof in support of embracing hypothesis H4, similar results were deducted by (Hajam & Gahir, 2024). The fifth hypothesis (H5) states that BH had a significant impact on AIAp. The authors have examined the findings in Table 7 ($\beta = 0.140$; $t = 2.581$; $p = 0.01$) to support this theory. These findings provide empirical evidence in favor of accepting hypothesis H5, further strengthening the results of (Kaya et al., 2024). The last hypothesis of the study (H6) proposed that EC moderates the relationship between BH and AIAp. The findings in Table 7 ($\beta = 0.045$; $t = 0.825$; $p = 0.410$), suggest the rejection of H6, opposite to the findings by (Shum & Lau, 2024).

Table 8
Structural Model Results

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	Path coefficient β	T statistics (O/STDEV)	P values
AW -> ATT	0.114	0.115	0.041	0.114	2.786	0.005
FF -> ATT	0.421	0.421	0.050	0.421	8.406	0.000
RSK -> ATT	0.400	0.400	0.040	0.400	9.949	0.000
ATT -> BH	0.816	0.816	0.019	0.816	42.718	0.000
BH -> AIAp	0.140	0.146	0.054	0.140	2.581	0.010
EC x BH -> AIAp	0.045	0.040	0.055	0.045	0.825	0.410

Conclusion

This study highlights the intricate relationships among various factors influencing attitudes and behaviors toward AI. It establishes that AI awareness, facilitating factors, and perceived risks play pivotal roles in shaping individuals' attitudes toward AI. A positive attitude toward AI was further identified as a key driver of behavior toward AI which, in turn, directly impacts the application of AI technologies (Rahiman & Kodikal, 2024; Minkevics & Kampars, 2021). These findings underscore the interconnected nature of awareness, attitudes, and behaviors in fostering AI adoption. Interestingly, the study found that ethical concerns did not moderate the relationship between behavior toward AI and its application (Chedrawi & Howayeck, 2019). This suggests that while ethical considerations remain significant in broader discussions about AI, they may not directly influence how individuals' behaviors translate into practical AI applications within the context of this research. Overall, the findings enrich our understanding of the factors that drive

the acceptance and utilization of AI, emphasizing the need for awareness-building and supportive environments to cultivate positive attitudes and behaviors toward AI adoption.

Managerial and Theoretical Implications

It is recommended that academic instructors and other concerned authorities focus expansion efforts on programs that will raise the consciousness of the users of AI technologies (Mishra, 2019). That means by increasing awareness of people regarding the possibilities of AI or its positive impacts, organizations can entice people toward AI use, thereby helping it gain more usage (van Twillert et al., 2020). There is a need for organizations to put in place structures and necessary infrastructures that enhance individuals' engagement and integration of AI solutions. Indeed, attitudes toward AI can be shifted by improving and focusing on user interfaces, training, and how AI is integrated into organizational tasks or user experiences (Wenge, 2021). It is now imperative for managers to do all they can to address issues that people have regarding the risks associated with AI (Chedrawi & Howayeck, 2019). It can involve such things as explaining to users how their data would be collected, used, secured, or protected, and the ethical processes that would be followed, which may help alleviate users' concerns and help them adopt a positive attitude towards Artificial Intelligence (Aldosari, 2020). Organizations can develop marketing and engagement plans that build on these favorable perceptions to increase AI adoption. Therefore, more behavioral intentions toward AI can be achieved through pilot projects supported by testimonials or case studies that would provide evidence of the benefits of the use of AI (Choi, 2020). The study supports the practical application of the theoretical framework mapping attitudes and behavior especially when it comes to the implementation of AI. This enhances the evidence base for behavioral theories like the Theory of Planned Behavior and the Technology Acceptance Model. The Theory of Planned Behavior suggests that an individual's intentions to perform a behavior, influenced by their attitudes, subjective norms, and perceived behavioral control, predict their likelihood of engaging in that behavior, confirmed by the current study's findings. The Technology Acceptance Model suggests that an individual's intention to use technology is determined by their perceived usefulness and perceived ease of use, which together influence actual usage behavior, confirmed by the findings of the current study. The research results indicate that contextual factors that have been deemed essential in determining the acceptance of AI include facilitating conditions and perceived risk. This implies that future research should explore more context-specific factors that affect AI adoption.

Limitations and Future Research Direction

A limitation is that the study included participants from one city. The results of the study may therefore not be quite generalizable to other geographic locations, industry sectors, or population segments. It means that cultural, economic, or social aspects might affect the perception of AI and related activities in various ways depending on the specific environment. Also, the study adopted a cross-sectional research design, which constrains its capacity to establish causality between variables. Cross-sectional research was used due to financial and time constraints. Future studies may utilize longitudinal research to understand changes in attitude/behavior towards AI over time. The data gathered mainly revolved around the existing awareness, factors that supported the process, perceived risks, and ethical issues. Other psychosocial factors were considered but not included in the study. These include trust, emotions, and social norms. These factors can be included in future studies to better predict mechanisms underlying AI application processes.

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Annexure I

Ethical Concerns	Adapted from (Fui-Hoon Nah et al., 2023)
EC1	Users adopt answers by generative AI without careful verification or fact-checking
EC2	Generative AI can be used for cheating in examinations or assignments
EC3	Plagiarism for assignments and essays using texts generated by AI
EC4	Generative AI may disclose sensitive or private information
EC5	Content produced by generative AI could be violent, offensive or erotic
Application of AI	Adapted From (Rahiman & Kodikal, 2024)
AIAp1	I apply AI technology to create teaching material and content development.
AIAp2	I apply AI tools to review homework, tests, and other written assignments, monitor student achievement, and provide feedback.
AIAp3	I apply AI tools to detect plagiarism in student papers and course works.
AIAp4	The application of AI in my higher education academic journey is cost-effective.
AIAp5	I am using AI technologies and tools in my teaching and learning activities
Behavior Toward AI	Adapted From (Rahiman & Kodikal, 2024)
Bh1	I believe AI technology is very easy to learn for beginners.
Bh2	I shall recommend all the stakeholders in higher education explore AI.
Bh3	I am willing to use AI technology for developing smart content.
Bh4	I intend to use AI technology for teaching-learning purposes in the next couple of years.
Bh5	I believe AI technology could be used to answer student's queries.
Attitude Toward AI	Adapted from (Rahiman & Kodikal, 2024)
Att1	I can learn AI technology quickly.
Att2	AI technology is useful for teaching-learning activities.
Att3	Using AI technology for query answering is a good idea.
Att4	People should learn AI technology for the future needs of the higher education sector.
Att5	AI technology can cater to individual needs more accurately.
Perceived Risks in AI Adoption	Adapted from (Rahiman & Kodikal, 2024)
Rsk1	I am aware of ethical aspects related to AI applications.
Rsk2	I believe AI-powered educational content is not always correct.
Rsk3	The application of AI for admission purposes is confusing.
Rsk4	I shall not prefer to use AI applications for administrative purposes.
Facilitating Conditions	Adapted from (Rahiman & Kodikal, 2024)
FC1	My institute has all the necessary resources to use AI technology for smart.
FC2	I have all the required resources to develop AI-based smart content.
FC3	My institute sponsors any AI-related learning opportunity.
FC4	All the classrooms of my institute are equipped with the necessary devices for using AI technology for teaching purposes.
FC5	My institute encourages its staff to use modern technology.
FC6	My institute has all the necessary resources to use AI technology for smart.
AI Awareness	Adapted from (Rahiman & Kodikal, 2024)
Aw1	I am familiar with data transformation and artificial intelligence-based academic tools.
Aw2	Artificial Intelligence tools are highly useful to prepare educational content and materials.
Aw3	AI-based technology like a chatbot quickly provides information and answers queries about academic affairs.
Aw4	I am aware of the application of AI-based technology in routine academic activities.