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Perceptual assessment of artificial intelligence assisted learning systems among students

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ABSTRACT

Incorporation of artificial intelligence (AI) in educational settings has transformed education through adaptive systems and intelligent tools. However, students' perceptions remain critical for understanding the adoption and utilization of AI-powered learning platforms. This research examines determinants of student perceptions by extending the technology acceptance model (TAM) to include trust in AI (TRUSTIA), perceived usefulness (PU), ethical concerns (EC), and perceived risk (PR). Partial least squares structural equation modeling (PLS-SEM) with bootstrapping 5,000 subsamples was used to assess the quantitative data gathered from university students. Research findings indicate that PU significantly influences both behavioral intentions towards AI assisted learning (BIASL) (β=0.240, $p<0.001$) and TRUSTIA (β=0.222, $p<0.001$). TRUSTIA shows a negative but minimal significant effect on BIASL (β=−0.197, p=0.050). EC strongly and positively affect BIASL (β=0.695, $p<0.001$) and significantly increase PR (β=0.162, $p<0.001$). However, PR does not significantly affect BIASL (β=0.118, p=0.227). The findings highlight PU and EC as key drivers of behavioral outcomes, with trust playing a mitigating role. The findings emphasize the essence of ethical considerations in adoption of AI in education.

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1. INTRODUCTION

Integration of artificial intelligence (AI) into higher education has rapidly transformed the learning landscape by enabling adaptive instruction, personalized feedback, and interactive academic support [1]. As AI-assisted learning systems become increasingly prevalent, understanding how students perceive these technologies is fundamental to their successful adoption and sustained use. Students who doubt the value of an AI tool, or distrust it, tend to abandon it no matter how capable the system is. However, recent empirical studies demonstrate that students' perceptions of AI tools particularly generative AI and intelligent tutoring systems, significantly influence learning outcomes and behavioral intentions (BIs) to use such systems. Prior research consistently identifies perceived usefulness (PU), perceived ease of use, and trust as key determinants of AI adoption [2]. However, there is a limited consensus on the roles of trust and ethical concerns (EC) in forming students' attitudes and BIs. This gap is particularly evident in AI-assisted learning

contexts, where the autonomous and opaque nature of AI systems introduces additional uncertainties beyond traditional usability and performance considerations. The technology acceptance model (TAM) asserts that PU and perceived ease of use are fundamental elements influencing the desire to accept technology [3]. In higher education, PU reflects students' views that AI tools improve learning effectiveness and academic success [4]. However, the applicability of traditional models such as TAM is increasingly questioned in AI contexts due to the opaque and autonomous nature of these systems, which introduce concerns related to trust, ethics, and risk [5]. Explainability and data handling receive little attention in the acceptance measures these models rely on. Consequently, performance-based factors alone are insufficient to explain user behavior. A student may agree that an AI tutor performs well and yet still hesitate to rely on it.

This work aims to remedy this gap by proposing an integrated model that extends TAM and protection motivation theory (PMT) by incorporating trust, perceived risk (PR), and, EC offering more comprehensive explanation of adoption of AI-assisted learning systems by students. Therefore, the research aims to: i) examine the impact of PU on students' behavioral intentions towards AI assisted learning (BIASL); ii) investigate the mediating role of trust in AI (TRUSTIA) in the between PU and BIs; iii) examine the effect of EC on PR; and iv) assess the mediating role of PR between EC and BIASL. These objectives offer a comprehensive understanding of the elements influencing students' engagement with AI-assisted learning technologies and aim to guide the creation of more successful solutions, ethical, and user-centered educational solutions. This study makes important contributions theoretically, to advances existing adoption models by integrating ethical and trust-related constructs, consequently offering a more thorough understanding of the integration of AI in education. It provides direction for educators and tech developers to build educational platforms with AI support that are both effective and morally accountable, hence enhancing user trust. The study underscores the necessity for legal frameworks that guarantee data privacy, equity, transparency, and responsible AI utilization, while also fostering digital literacy and ethical consciousness among students.

2. THEORETICAL REVIEW

2.1. Relevant theories

2.1.1. Extended technology acceptance model

The TAM, initially introduced by Syahmi *et al*. [5], continues to be a crucial paradigm for elucidating technology acceptance. PU and perceived ease of use have an impact on consumers' attitudes and BIs about technology use, according to the TAM. Regarding AI-assisted learning, PU denotes students' convictions that AI systems augment academic achievement, boost efficiency, and facilitate learning outcomes. Recent empirical studies affirm the ongoing significance of the TAM in AI-enhanced education. For instance, studies in education and information technologies [6]. demonstrate that PU remains the most significant determinant of students' disposition to use generative AI application in higher education. Similarly, Jamaluddin *et al*. [7] shows that performance-related beliefs significantly determine student engagement with AI tutoring systems. However, Bagozzi [8] argued that TAM insufficiently accounts for emotional, social, and moral dimensions of technology use. In AI contexts, this limitation becomes more pronounced because AI systems operate autonomously and often lack transparency. A student cannot always tell why the system produced a recommendation, so judgments about ease of use say little about whether the tool deserves confidence. TAM alone cannot fully explain AI adoption without incorporating psychological and ethical dimensions. Thus, while extended TAM provides the structural backbone for explaining BIASL, it requires theoretical enrichment to address AI-specific complexities.

2.1.2. Trust theory

Trust theory addresses the relational dimension absent in traditional TAM models. According to Mayer *et al*. [9], "trust is grounded in perceptions of ability", benevolence, and integrity. In AI systems, these dimensions translate into beliefs about algorithmic competence, fairness, and transparency. Recent study by Omrani *et al*. [10] emphasizes that trust is particularly critical in AI-driven environments due to algorithmic opacity and perceived lack of human oversight. Research by Araujo *et al*. [11] demonstrates that trust significantly "mediates the relationship between PU and intention" to use AI systems. Similarly, study by Bodó [12] highlight that students' confidence in AI reliability directly predicts their readiness to engage with AI-supported education platforms. The reverse also holds: a single experience of biased or inaccurate output can erode confidence built over months. Importantly, trust functions not just as an additional predictor but also as a strategy for risk reduction. As Gefen *et al*. [13] argue, trust mitigates perceived uncertainty in digital environments. When students believe the system is competent and fair, they are more willing to accept outcomes they cannot verify for themselves. In AI-assisted learning systems where automated decision-making may affect grading or feedback trust becomes foundational for acceptance.

2.1.3. Protection motivation theory

The ethical risk perspective, adapted from PMT, introduces threat appraisal into the adoption model. PMT suggests that individuals evaluate the severity and vulnerability associated with potential risks before deciding to adopt or avoid a behavior. Adoption in this view depends on more than expected benefit; the individual also weighs what could go wrong and how badly. In AI-assisted learning contexts, EC and PR represent students' cognitive assessments of privacy violations, algorithmic bias, data misuse, and academic integrity implications. The integration of extended TAM, trust theory, and the ethical risk perspective reflects a shift from single-theory explanations toward multidimensional AI adoption frameworks, as advocated in recent literature [14]. This integrated theoretical positioning advances prior AI-in-education research by addressing the fragmented treatment of trust and ethics in TAMs. Table 1 shows the details for the integrated theories used in this study with their respective variables. The model offers a thorough explanation of AI adoption by combining extended TAM, trust theory, and PMT. PU drives BI, trust reduces uncertainty and strengthens acceptance, while EC increase PR and may hinder adoption. Together, these factors capture both enabling and inhibiting influences on students' use of AI-assisted learning systems.

Table 1. Integrated theories used in this study

Sources	Theories	Context	Variables
[15]	Extended TAM	It explains technology adoption based on students' perceptions of usefulness and ease of use.	BIASL, PU
[16]	PMT	Ethical risk theory (adapted from PMT) captures perceived threats and risks, which may hinder adoption.	EC PR
[17]	Trust theory	(Trust addresses students' confidence in AI reliability, fairness, and transparency, particularly in opaque AI systems)	TRUSTIA

2.2. Empirical review

2.2.1. Artificial intelligence

AI applications including adaptive tutoring systems, automated feedback mechanisms, predictive analytics, and generative AI are rapidly reshaping higher education. Recent scholarship highlights AI's potential to enhance personalization, scaffold learning, and improve performance outcomes. Generative AI systems in particular have accelerated institutional adoption debates, prompting reconsideration of assessment practices, pedagogical design, and digital literacy [18]. However, empirical findings suggest that student adoption is not uniformly positive. While learners acknowledge AI's academic benefits, they simultaneously express concerns regarding bias, privacy, transparency, and academic integrity [19]. This duality indicates that AI decisions about adoption are shaped by both benefit appraisal and risk appraisal processes. The same student who praises an AI tutor for faster feedback may also worry about where the submitted essay is stored and who can see it. Consequently, explanatory models must extend beyond traditional performance-based acceptance theories. To address this complexity, the current research integrates extended TAM, trust theory, and ethical risk perspective derived from PMT.

2.2.2. Trust in artificial intelligence systems

Trust is foundational in environments characterized by uncertainty and limited transparency. Study by Fraga-Lamas *et al*. [20] conceptualize trust as willingness to embrace vulnerability contingent upon perceptions of ability, benevolence, and integrity. In AI-assisted learning, trust reflects students' confidence that the system is reliable, unbiased, and operates transparently. Unlike traditional educational software, AI systems frequently rely on opaque algorithms. This "black-box" nature heightens perceived uncertainty. Students are asked to act on outputs whose reasoning they cannot inspect, which raises the stakes of any misplaced confidence. In AI contexts, recent interdisciplinary research reinforces the importance of trust [21]. The study emphasizes that trust is central to responsible AI adoption, particularly in data-intensive systems. Where trust is high, students are more likely to convert positive performance beliefs into actual usage intentions. Conversely, low trust can suppress adoption even when PU is strong. Importantly, trust operates not only as an independent predictor but also as a stabilizing mechanism within complex socio-technical systems. In educational AI environments, trust reduces perceived vulnerability associated with algorithmic grading, automated feedback, and data surveillance. Therefore, integrating trust theory addresses a critical limitation of TAM by capturing relational and psychological assurances necessary for AI acceptance.

2.2.3. Ethical risk perspective

While TAM explains benefit-driven adoption, it does not fully account for threat evaluation. PMT, proposes that individuals assess both threat severity and vulnerability before deciding whether to engage in or

avoid a behavior [22]. In AI-assisted learning, EC and PR represent threat appraisal mechanisms. EC may include data privacy breaches, algorithmic bias, lack of explain ability, and academic misconduct risks. PR reflects anticipated negative consequences associated with AI use. For a student, such consequences might include an unfair automated grade or the exposure of personal information to third parties. Recent study underscores the salience of these concerns and highlight risks related to misinformation, bias amplification, and dependency [23]. It further argues that governance and accountability concern significantly shape user attitudes toward generative AI.

2.3. Hypothesis development

PU and BI toward AI-assisted learning: PU, a fundamental element of the TAM model, elucidates the extent to which students perceive AI-assisted educational platforms improve their academic performance and learning outcomes. In educational settings, PU denotes perceived advantages of AI tools, including adaptive tutoring systems, generative AI platforms, and intelligent feedback mechanisms, in enhancing productivity, comprehension, and efficiency [14]. Students who believe AI technology is beneficial are more inclined to use it for educational purposes. The judgment is practical: it rests on whether the tool saves time and helps the student understand the material. Multiple studies highlight the critical impact of PU on students' BIs, suggesting that students are more inclined to use AI technology when they recognize academic advantages, such as customized feedback and automated support. Previous research corroborates that PU strongly affects students' propensity to incorporate AI into their academic processes, especially when these technologies improve engagement, problem-solving, and job efficiency [24]. Recent research indicates that AI systems are more readily embraced when regarded as academically beneficial and capable of enhancing learning efficiency. The findings identify perceived utility as a crucial factor in AI adoption, with students demonstrating a greater propensity to utilize technology that enhance performance, diminish cognitive load, and facilitate academic achievement. Considering these discoveries, the study posits the following hypothesis: PU has statistically positive significant effect on students' BI to use AI-assisted learning systems (H1).

2.3.1. Perceived usefulness and trust in artificial intelligence

PU has been extensively acknowledged as a crucial factor influencing technology acceptability within the TAM. In AI-assisted learning environments, PU denotes students' convictions that AI technologies may augment their academic achievement, promote learning efficiency, and offer significant academic assistance. When students recognize AI systems as advantageous and effective in enhancing their learning experiences, they are more inclined to cultivate confidence in the technology [12]. Empirical studies in educational technology indicate that the perceived benefits of AI tools strongly influence users' trust perceptions. research by, indicates that students who perceive generative AI applications as useful for academic tasks are more inclined to develop trust in these technologies for research and learning activities [25]. Their findings suggest that PU enhances trust because students interpret the functional capabilities of AI such as content generation, academic summarization, and knowledge support as indicators of technological reliability and competence. AI-based systems that provide adaptive learning pathways, automated feedback, and intelligent tutoring significantly improve students' perceptions of usefulness, which subsequently strengthens their trust in the system's capability to support learning outcomes. Drawing on these empirical findings, this study proposes and articulates the following hypothesis: PU has statically positive significant effect on students' TRUSTIA-assisted learning systems (H2).

2.3.2. Artificial intelligence trust and behavioral intentions toward artificial intelligence-assisted learning

TRUSTIA as key elements influencing students' acceptance and sustained use of AI-assisted learning systems. It reflects students' trust in the dependability, transparency, fairness, and competence of AI technology acts as a psychological mechanism to reduce uncertainty and enhance reliance on these systems. As AI tools increasingly perform complex tasks such as automated feedback, content generation, and adaptive learning, trust becomes essential for fostering student engagement. A student who trusts the system will act on its feedback; one who does not will second-guess even correct output. Empirical studies consistently show that trust significantly predicts students' motivation to accept AI-based educational technologies. Similarly, observed that trust had a substantial influence on students' inclination to employ generative AI tools for educational purposes, as it strengthens confidence in the accuracy and integrity of AI-produced results. According to Gu *et al*. [26], students are likely to accept AI platforms when they trust their ability to provide accurate and fair outcomes. High levels of trust encourage reliance on AI for personalized learning and academic support, whereas low trust can lead to skepticism and resistance [11]. Drawing on these empirical findings, this research present hypothesis: TRUSTIA has statistically positive significant effect on students' BI towards AI-assisted learning systems (H2.1).

2.3.3. Ethical concerns and behavioral intentions toward artificial intelligence-assisted learning

EC have become a significant determinant in the use of AI in educational settings, particularly as these technologies increasingly interact with students' learning processes and academic data. These concerns include data privacy, algorithmic bias, openness, academic integrity, and the fairness in making decision. As AI-assisted learning platform become more widespread, such ethical considerations can shape students' perceptions and motivate their willingness to use these technologies. From the viewpoint of PMT, EC may act as perceived threats that lead to negative attitudes and reduced intention to use AI systems. Amanso and Owan [27] provide strong evidence that EC influence students' adoption behavior, show that concerns about data security, algorithmic bias, and potential misuse of AI systems can discourage adoption, as students may perceive such technologies as ethically problematic and risky. According to Fraga-Lamas *et al*. [20], concerns about fairness and transparency may undermine TRUSTIA systems, leading to skepticism and resistance. In light of these empirical findings, the current study posits the following hypothesis: EC have statistically positive significant effect on students' BI to use AI-assisted learning systems (H3).

2.3.4. Ethical concerns and perceived risk

Ethical issues and risk perception are intertwined in the use of AI notably in educational settings. Moral concerns such as substances related to algorithmic bias, privacy, transparency and academic integrity often shape students' perceptions of potential dangers in line with AI platforms. Drawing on PMT, these concerns can act as perceived threats that trigger risk evaluations, leading students to view AI technologies as potentially harmful and thus reducing willingness to adopt [16]. Empirical studies support this relationship by showing that EC significantly influence PR. For instance, Dhiman *et al*. [28] found that ethical awareness and perceived ethical vulnerabilities increase students' perception of technological risk. In other words, the more clearly a student sees the ethical stakes, the more danger the same system appears to carry. Similarly, perceived hazards of data misuse, bias and lack of accountability in AI systems might raise concerns and thereby impact users' attitudes towards adoption. Further evidence highlights the role of EC in academic contexts. found that issues such as plagiarism, abuse of AI-generated material, and fairness in automated systems increase students' PRs, including concerns about accuracy and academic performance: EC have statically positive significant effect on students' PR of AI-assisted learning systems (H4).

2.3.5. Behavioral intentions toward artificial intelligence-assisted learning platform and perceived risk

PR is a key factor impacting the use of AI-assisted learning platform, referring to students' assessment of potential negative outcomes such as data privacy issues, misinformation, overreliance on AI, and academic integrity apprehensions. As AI technologies become increasingly embedded in education, these PRs are a major force in affecting students' preparedness to use such platforms. From the perspective of PMT, higher PRs can trigger protective behaviors, leading students to avoid or limit their engagement with AI tools. Avoidance here is a form of self-protection, the same response people show toward any technology they expect to harm them. Prior research evidence supports the negative influence of PR on technology adoption. Li [29] found that ethical and technological risks, including concerns about bias, data security, and transparency, can discourage students from adopting AI systems. As studies have also highlighted "the impact of PR on trust and usage intention; showed that concerns about the reliability and credibility of AI-generated content" increase PR and reduce adoption intentions. PR serves as a key impediment to adoption of AI, as students are less likely to engage with technologies, they consider unreliable or potentially harmful to their academic performance and privacy [23]. With these empirical insights, this study presents the following hypothesis: PR have statically negative significant effect on students' BI to use AI-assisted learning systems (H4.1) and subsequently provides the given conceptual framework as illustrated in Figure 1.

Notwithstanding the empirical research on AI-assisted learning, numerous critical gaps remain. Existing studies predominantly adopt a benefit-oriented perspective, focusing on PU and performance outcomes, while giving limited attention to the combined impact of EC, trust, and risk perception in student BIs. Moreover, the interrelationships among these constructs particularly the mediating roles of trust and PR are insufficiently explored, with trust rarely examined as a mechanism linking cognitive perceptions to behavioral outcomes. This highlights the need for multidimensional frameworks that integrate cognitive, psychological, and ethical dimensions. The key novelty of this study resides in its integrative and multidimensional approach to AI adoption in education. It uniquely combines cognitive (PU), relational (TRUSTIA), and ethical risk factors (EC and PR) within a single framework, moving beyond fragmented, single-factor models. The study enhances understanding through exploring the mediating roles of trust and PR, which provides more insight into indirect and non-linear relationships. Additionally, the study rigorously tested the complex interactions within the specific context of AI-assisted learning systems. By treating trust and PR as intervening variables rather than simple predictors, the model can account for why favorable views of AI do not always translate into actual use. It also helps explain cases where students who find a tool useful still hesitate to rely on it.

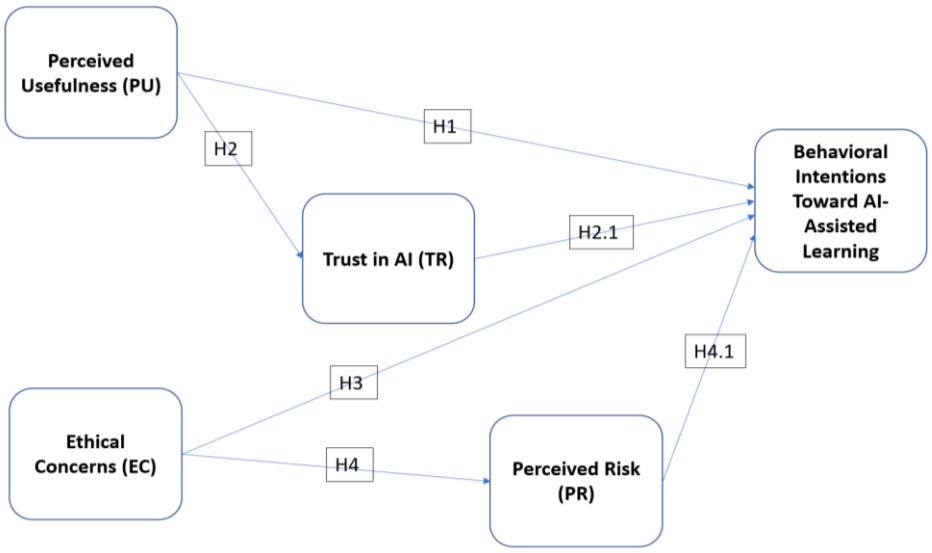


Figure 1. Conceptual framework for the study

3. METHOD

3.1. Data collection

This research was carried out during January and February 2026 by means of a structured online survey administered to university students who actively utilized AI-assisted learning technologies, including generative AI tools, systems for intelligent instruction, and AI-supported educational platform. Prior to data collection, institutional approval and the necessary authorization were obtained from the participating institution to ensure ethical compliance. Data was collected via online surveys from students in higher education institutions. Respondents were recruited through institutional communication channels, including university email platforms and students' WhatsApp group platforms commonly used for academic communication. The Google Forms survey link was shared electronically through these channels, enabling participants to access and complete the questionnaire voluntarily and remotely. To ensure the relevance of responses, participants had to be registered students having prior exposure to AI-assisted educational technologies, intelligent tutoring systems, generative AI tools, or AI-supported educational platforms, in order to meet the inclusion criteria. Distributing the questionnaire through channels the students already checked daily reduced the effort needed to take part and improved the response rate. Because participation was optional and no identifying details were requested, respondents could answer candidly without worrying that their views would be traced back to them.

3.2. Research design

The study adopts a quantitative cross-sectional procedure to investigate the perceptions and BIs of students on AI-assisted learning platforms. The method was employed to gather data from university students with previous experience utilizing AI in academic environment. The use of quantitative design is well-founded, since it allows for the systematic examination of hypothesized correlations across latent dimensions and promotes the statistical generalization of findings in technology adoption research. The cross-sectional approach facilitates easy data gathering from a substantial sample at a single moment, rendering it appropriate for collecting current perceptions and behavioral trends about swiftly advancing technology like AI. Notwithstanding these advantages, the research design possesses specific constraints. Because data are collected at a single point in time rather than over multiple time intervals, the cross-sectional form of the study restricts the ability to infer causal associations. Moreover, reliance on self-reported survey information may result into common method bias and social desirability influences. A single round of measurement was practical given the time and access available for the study, and it captured how students felt about these tools at a stage when the technology itself was still shifting. Later work could revisit the same students to see whether their views hold over time.

3.3. Population and sample size

University students that actively use AI-powered platforms like generative AI, intelligent teaching systems, and AI-supported platforms are the target population. These students were chosen because their

direct experience makes them suitable for providing insights into perceptions and experiences with these technologies. Participants were selected by purposive sampling to ensure that the respondents had previous experience with AI-assisted learning and the specific knowledge necessary for the research. Sample size determination was conducted using two different approaches for partial least squares structural equation modeling (PLS-SEM) analysis:

- 10-times rule: minimum sample must be 10x the largest number of structural paths to an endogenous construct.
- A priori power analysis: based on four predictors of the endogenous construct BIASL, with medium effect size f^2=0.15, α=0.05, and power=0.80, the minimum sample required is 85 respondents.

The actual sample used is 486 which exceeds both thresholds, ensuring sufficient statistical power and robust, reliable model estimates. Recruiting only students who had already worked with these systems meant the answers came from people describing real use rather than guesswork. The final count of 486 also left room to set aside incomplete responses without falling below the required minimum.

3.4. Instrumentation and data collection

A questionnaire was used as principal tool for gathering data on students' perceptions of AI-assisted learning systems. The instrument was created utilizing proven measuring scales modified from previous studies to guarantee consistency and content relevance. The survey was segmented into two parts. Section A captured respondents' demographic characteristics, including gender, age, academic level, and frequency of AI technology usage. Section B comprised measurement items assessing the major constructs of the study, namely PU, TRUSTIA, EC, BI, and PR. All measurement items were evaluated via a Likert scale, with 1 representing strongly disagree and 5 denoting strongly agree. The instrument underwent expert assessment by specialists in information systems and analytics to establish content validity, and reliability analysis demonstrated Cronbach's alpha values exceeding 0.70, signifying adequate internal consistency. Furthermore, measurement items were refined for clarity and suitability before final administration. Additionally, throughout the data gathering procedure, respondents were guaranteed anonymity, confidentiality, and voluntary participation. Splitting the questionnaire into a short background section and a longer set of construct items kept it easy to follow and helped hold respondents' attention to the end. Borrowing items from studies that had already tested them meant each question had a track record before it reached the students.

3.5. Data analysis technique

The data were analyzed using PLS-SEM. The analysis was conducted in two primary steps: the assessment of the measurement model and the evaluation of the structural model. The measuring model was examined to determine the reliability and validity of constructs based on the following criteria. Reliability of the indicators: factor loading >0.70. Internal consistency reliability was assessed by Cronbach's alpha and composite reliability (CR) values greater than 0.70. Convergent validity is determined by average variance extracted (AVE) should be more than 0.50. The discriminant validity is evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT). Prior to testing of research hypotheses, the measurement model was evaluated and found to be appropriate. Then, the structural model was evaluated. The following criteria were used: associations were determined by path coefficients (β) which indicate magnitude and direction of association. Assessment of the explanatory power and predictive relevance Q^2 through coefficient of determination R^2 among others, using the blindfolding procedure. This procedure enables a holistic investigation of the relationship between perceived utility, TRUSTIA, ethical considerations, PR, and students' willingness to interact with AI applications. Running the measurement checks before touching the hypotheses meant that any weak indicators were caught early, so the structural results rested on constructs that had already earned their place.

4. DATA ANALYSIS AND RESULTS

The respondents' demographic profile shows a distribution of gender that is comparatively balanced with 51.9% female and 48.1% male participants. A large number of responses were in the 18–25 age group (42.0%), followed by those aged 26–30 (27.4%), suggesting that the sample is largely composed of young adults actively engaged in higher education. The majority of participants possesses undergraduate degrees (67.3%), with smaller proportions at the postgraduate (22.0%), diploma (8.8%), and doctoral (1.9%) levels. Regarding AI usage, the findings reveal a high level of engagement with AI tools among respondents. A significant proportion reported using AI multiple times a day (40.7%) or daily (31.9%), indicating strong familiarity and reliance on AI-assisted technologies. Hence, the sample reflects a population with substantial exposure to AI tools in academic contexts. Table 2 shows the details on the demographic attributes.

Table 2. Demographic variables

Variables	Category	Frequency	Percentages (%)
Gender	Male	234	48.1
	Female	252	51.9
Age	Under 18	42	8.6
	18-25	204	42.0
	26-30	133	27.4
	31-40	53	10.9
	Above 40	54	11.1
Education	Diploma	43	8.8
	Undergraduate	327	67.3
	Postgraduate	107	22.0
	Doctorate	9	1.9
Average frequency usage of AI tools	Rarely	19	3.9
	Daily	155	31.9
	Multiple times in a day	198	40.7
	1-2 times per week	50	10.3
	3-5 times per week	64	13.2

4.1. Measurement models

The measurement assessment was evaluated using SmartPLS 4 to assess the validity and reliability of the study constructs in compliance with accepted PLS-SEM guidelines. The assessment followed a three-step procedure: evaluation of indicator loadings and internal consistency reliability, assessment of convergent validity, and examination of discriminant. The procedures ensure that the observed indicators satisfactorily signify the corresponding latent constructs and meet the required psychometric criteria for PLS-SEM analysis. Indicator reliability was examined using outer loadings generated in SmartPLS 4. Consistent with recommended thresholds, most indicator loadings exceeded 0.708, indicating satisfactory item reliability [30]. Retaining items at this level meant that each surviving indicator shared enough variance with its construct to be treated as a dependable measure, and the few items that fell short were reviewed rather than kept by default. Internal consistency was examined with Cronbach's alpha, CR (ρC) and Dijkstra-Henseler's rho (ρA). All the constructs showed values over the predetermined threshold of 0.70, confirming acceptable levels of reliability. Reporting all three reliability measures together, rather than leaning on a single coefficient, gives a fuller picture of how consistently the items behaved and guards against the known limits of any one statistic taken on its own, as shown in Table 3.

Table 3. Indicator loadings and internal reliability

Variables	Items	Loadings	Cronbach's alpha	(rho_a)	(rho_c)	AVE
BIASL	BIASL1	0.867	0.925	0.925	0.947	0.816
	BIASL2	0.909				
	BIASL3	0.919				
	BIASL4	0.918				
EC	EC1	0.749	0.848	0.864	0.898	0.688
	EC2	0.903				
	EC3	0.812				
	EC4	0.847				
PRISK	PRISK1	0.91	0.805	0.846	0.884	0.719
	PRISK2	0.784				
	PRISK3	0.845				
PU	PU1	0.818	0.916	0.925	0.940	0.798
	PU2	0.913				
TRUSTIA	TRUSTIA1	0.879	0.902	0.930	0.933	0.780
	TRUSTIA2	0.715				

4.1.1. Discriminant validity

Discriminant validity is the degree to which a construct differs experimentally from other items in the model. The discriminant validity is verified according to the Fornell–Larcker criterion when the square root of the AVE of each construct is greater than its correlations with other constructs. As shown in Table 4, the AVE values for all constructs satisfied this requirement, affirming adequate discriminant validity under the Fornell–Larcker assessment. Additional verification was conducted through the examination of cross-loadings. As seen in Table 5, all indicators show higher loadings on the various constructs (bolded values) than on any other constructs, further supporting discriminant validity. Moreover, discriminant validity may be compromised when the HTMT exceeds 0.900, indicating a lack of distinction between

constructs [30]. The HTMT results in Table 6 show all values were below 0.900 threshold, providing additional evidence of satisfactory discriminant validity.

Table 4. Fornell Larcker

Construct	BIASL	EC	PRISK	PU	TRUSTIA
BIASL	0.903				
EC	0.827	0.830			
PRISK	0.085	0.162	0.848		
PU	0.615	0.572	0.179	0.893	
TRUSTIA	0.055	0.125	0.954	0.222	0.883

Table 5. Cross-loadings

Indicators	BIASL	EC	PRISK	PU	TRUSTIA
BIASL1	0.867	0.755	0.099	0.616	0.086
BIASL2	0.909	0.691	0.026	0.613	0.005
BIASL3	0.919	0.774	0.056	0.463	0.015
BIASL4	0.918	0.764	0.123	0.522	0.088
EC1	0.607	0.749	0.044	0.478	0.03
EC2	0.786	0.903	0.152	0.556	0.116
EC3	0.735	0.812	0.206	0.477	0.166
EC4	0.576	0.847	0.112	0.363	0.082
PRISK1	0.086	0.166	0.910	0.148	0.861
PRISK2	0.082	0.125	0.784	0.110	0.678
PRISK3	0.038	0.110	0.845	0.213	0.908
PU1	0.612	0.682	0.222	0.818	0.240
PU2	0.586	0.458	0.197	0.913	0.246
TRUSTIA1	0.097	0.153	0.904	0.158	0.879
TRUSTIA2	0.127	0.157	0.785	0.137	0.715

Table 6. HTMT

Construct	BIASL	EC	PRISK	PU	TRUSTIA
BIASL					
EC	0.920				
PRISK	0.095	0.182			
PU	0.652	0.624	0.204		
TRUSTIA	0.095	0.147	1.138	0.229	

4.1.2. Multicollinearity assessment

To ensure that indicators do not show significant collinearity that could skew parameter estimations, collinearity were assessed with variance inflation factor (VIF). Following recommended thresholds, values of VIF below 5.0 (or more conservatively 3.3) indicate acceptable levels of collinearity. While the measurement model demonstrates acceptable collinearity for most indicators, the presence of extreme VIF values suggests potential model misspecification, as seen in Table 7.

Table 7. VIF

Construct	Value
BIASL1	2.422
BIASL2	3.663
BIASL3	3.753
BIASL4	3.996
EC1	1.539
EC2	3.209
EC3	1.699
EC4	2.748
PRISK1	2.392
PRISK2	1.41
PRISK3	2.264
PU1	1.857
PU2	3.209
TRUSTIA1	2.75
TRUSTIA2	1.515

4.2. Structural model assessment

The structural assessed was done using recognized procedures; paths were evaluated using a bootstrapping technique with 5,000 subsamples, as demonstrated in Figure 2 and Table 8. The research hypothesizes that PU considerably and favorably affects students' predisposition to adopt AI-assisted learning tools. The results indicate a statistically positive significant correlation between PU and the intent of using AI-assisted learning systems (β=0.240, t=6.883, p=0.000). This implies PU significantly enhances intention. Educators should prioritize demonstrating the academic value of AI tools by embedding them into core learning activities, such as research support and problem-solving tasks and to further help students understand how these tools improve learning efficiency and outcomes, thereby strengthening adoption. Because usefulness is among the more visible qualities of a tool, the result is a reminder that students weigh what a system does for them before folding it into their routine. In H2, it also indicates that PU has a positive significant effect on students' TRUSTIA-assisted learning systems. The findings reveal a positive significant relationship between PU and TRUSTIA-assisted learning systems β=0.222, t=6.099, p=0.000), this suggests institutions should foster trust through hands-on training, transparent use of AI systems, and the provision of institutionally verified platforms. In H2.1 the proposed; TRUSTIA has a positive significant effect on students' intention to use AI-assisted learning systems. However, the finding reveals a negative significant relationship between TRUSTIA and BI to use AI-assisted learning systems (β=-0.197, t=1.957, p=0.050). This suggests that increased TRUSTIA awareness may lead to more cautious usage. This therefore underscores the need to promote critical AI literacy, encouraging students to verify outputs and engage with AI in a balanced and reflective manner rather than relying on it uncritically.

H3 further proposed that EC have a positive significant effect on students' intention of using AI-assisted learning applications. The findings show a strong positive effect of EC on BI to use AI-assisted learning systems (β=0.695, t=21.572, p=0.000). This shows that ethically students are actively engaged in AI technologies. This highlights the importance of integrating AI ethics into curricula through modules, on issues such as bias, privacy, and academic integrity. The size of this effect stands out against the others, which points to ethics sitting closer to the front of students' minds than a purely convenience-driven account would predict.

Again, in H4 proposes that EC have a significant positive effect on students' PR of AI-assisted learning systems. The findings reveal a positive significant relationship between EC and PR (β=0.162, t=4.757, p=0.000). suggesting that institutions must address these concerns by providing clear guidelines on data privacy, ensuring transparency in AI systems, and communicating risk mitigation strategies. However, in H4.1 the study proposed that, PR has a significant negative effect on students' intention of using AI-assisted learning applications. The finding shows a significant positive effect between PR BI to use AI-assisted learning systems (β=0.118, t=1.209, p=0.227). This suggest students acknowledge potential risks of AI but are not discouraged when clear benefits exist; therefore, educational strategies should be prioritized to enhance perceived value and ethical understanding rather than overemphasizing risk. universities should integrate AI literacy and ethics into curricula, establish balanced usage policies, invest in effective AI tools, and equip faculty with both technical and pedagogical skills to support critical and responsible AI use.

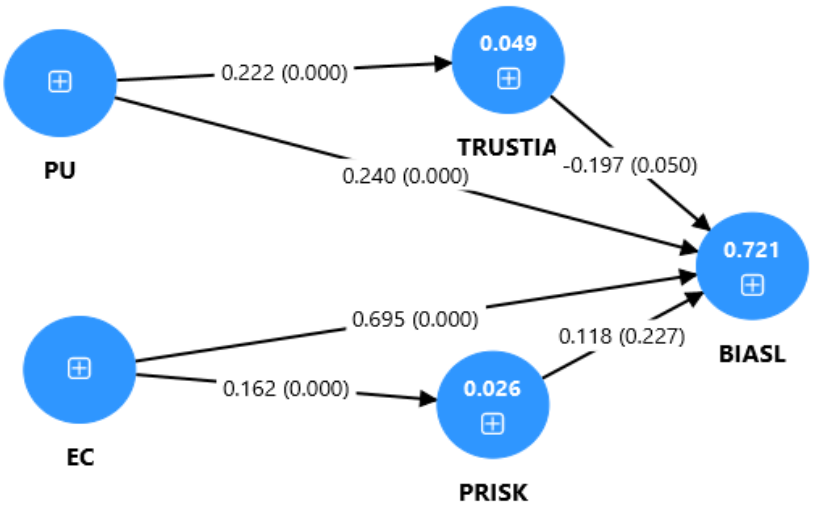


Figure 2. Final model analysis

Table 8. Path analysis

Hypothesis	Path	β	T statistics	P values	Significance
H1	PU->BIASL	0.240	6.883	0.000	YES
H2	PU->TRUSTIA	0.222	6.099	0.000	YES
H2.1	TRUSTIA->BIASL	-0.197	1.957	0.050	N/A
H3	EC->BIASL	0.695	21.572	0.000	YES
H4	EC->PRISK	0.162	4.757	0.000	YES
H4.1	PRISK->BIASL	0.118	1.209	0.227	N/A

4.3. Coefficient of determination (R^2)

Within a structural model, the coefficient of determination (R^2) quantifies the percentage of variance by dependent variable that is explained by its related independent variable. It serves as an important indicator of the model's predictive capability and is calculated as the squared correlation between the observed and predicted values of the endogenous variable. R^2 values range from 0 to 1, with higher values indicating stronger explanatory power. R^2 values of 0.75, 0.50, and 0.25 are interpreted as substantial, moderate, and weak, respectively [30]. In this study, the R^2 results presented in Table 6 show that BIASL (R^2=0.721) exhibits a substantial level of explanatory power, shows a large proportion of its change is explained by the predictors in the model. In contrast, PRISK (R^2=0.026) and TRUSTIA (R^2=0.049) display weak explanatory power, suggesting that only a small proportion of their variance is accounted for by the model. Inclusive, these results reveal that, while the model strongly explains BIASL, it has limited explanatory capability for PRISK and TRUSTIA, though it still demonstrates some predictive relevance.

The gap between these figures is worth reading carefully, since the model was built mainly to account for BI, so weaker explanation of the two secondary constructs sits closer to what the design anticipated than to a flaw in the estimates, as seen in Table 9. Predictive relevance was assessed using Q^2 predicts values. According to Majerova *et al*. [30], Q^2 values of 0.00, 0.25, and 0.50 indicate small, medium, and large predictive relevance, respectively. The results show that, BIASL (Q^2=0.714) demonstrates high predictive relevance, exceeding the 0.50 threshold. This indicates that the model has strong predictive capability for BIASL, suggesting that the exogenous constructs meaningfully explain and predict this variable.

In contrast, PRISK (Q^2=0.023) and TRUSTIA (Q^2=0.045) exhibit small predictive relevance, as their values are above zero but well below the 0.25 recommended. This implies that while the model has some predictive capability for these constructs, the explanatory power remains weak. The findings reveal that the model has strong predictive accuracy for BIASL but limited predictive capability for PRISK and TRUSTIA, highlighting potential areas for model improvement. Because Q^2 and R^2 tell a similar story, the two measures reinforce one another rather than pulling in different directions, giving more confidence that the pattern reflects the data rather than the quirks of a single index. Table 10 shows the detail for SRMR values (0.197 and 0.213) exceed recommended thresholds, indicating suboptimal model fit. Similarly, the elevated d_ULS values suggest potential model misspecification. However, consistent with PLS-SEM guidelines, model evaluation primarily emphasizes predictive accuracy; therefore, these results are interpreted alongside R^2 and Q^2 metrics.

Table 9. Coefficient of determination (R^2)

Variables	R^2	Consideration	Q^2 predict	Predictive accuracy
BIASL	0.721	Substantial	0.023	Small
PRISK	0.026	Weak	0.045	Small
TRUSTIA	0.049	Weak	0.714	Large

Table 10. Model fit

Fit indices	Saturated model	Estimated model
SRMR	0.197	0.213
d_ULS	8.132	9.568

4.4. Mediation analysis

The results consistently show that there are no mediation effects in the model, as shown in Table 11. Specifically, the relationship between ethical considerations and BI is not mediated by PR. (EC→PRISK→BIASL), as both the direct and indirect effects are insignificant despite a strong and significant total effect (β=0.714, p<0.000). This reflects a no-effect non-mediation scenario, suggesting that although students may express EC about AI-assisted learning systems, these concerns are not translated into

PRs that influence students' intentions towards AI-assisted applications. Similarly, TRUSTIA do not mediate the relationship between PU and BI (PU→TRUSTIA→BIASL), both the indirect and direct effects are also insignificant, even though the total effect is significant and positive (β=0.196, p<0.000). This reveal that while students may perceive AI systems as useful, such perceptions do not necessarily build trust or lead to usage intentions. The findings suggest that the proposed mediators PR and trust do not serve as effective explanatory mechanisms, pointing instead to the potential role of alternative mediating variables such as perceived ease of use, satisfaction, or impact on societal how students use AI-assisted learning platforms, as shown in Table 11.

Table 11. Mediation results

Path	Total effect		Direct effect		Path	Indirect effect	
	Path coefficient	P-values	Path coefficient	P-values		Path coefficient	P-values
EC->BIASL	0.714	0.000	0.019	0.266	EC->PRISK->BIASL	0.019	0.266
PU->BIASL	0.196	0.000	-0.044	0.089	PU->TRUSTIA->BIASL	-0.044	0.089

5. DISCUSSION

This study examined the factors influencing students' BI toward AI-assisted learning systems by integrating constructs from the TAM and PMT. The findings provide both confirmatory and unexpected insights into how PU, TRUSTIA, EC, and PR shape students' BIASL technologies [28]. The findings confirm that PU significantly and positively influences BI (H1), indicating that students are more likely to adopt AI-assisted learning systems when they perceive them as beneficial to their academic performance and learning efficiency. This finding is consistent with prior study that identify PU as a major determinant of technology adoption and continued usage [23]. In practical terms, this means the case for adoption is strongest when students can see a clear link between using a tool and doing better academic work, rather than adopting it for its own sake. Additionally, PU positively influences TRUSTIA (H2), suggesting that students are more likely to trust AI systems when they perceive them as reliable and academically valuable [26]. This supports the argument that system performance and effectiveness are important antecedents of trust formation in AI-enabled learning environments. However, TRUSTIA exhibits a negative and marginally significant effect on BI (H2.1), suggesting that increased trust may not necessarily lead to stronger adoption intentions. One possible explanation is that students who critically evaluate AI systems may become more aware of their limitations, biases, and ethical implications, resulting in more cautious usage [25]. This finding highlights the complex and non-linear role of TRUSTIA adoption, particularly in educational settings where transparency, fairness, and accountability are critical [29].

Trust is less a simple accelerator of use than a prompt for scrutiny, and students who trust a system enough to lean on it also seem to pay closer attention to where it can go wrong. The study further reveals that EC have a strong positive effect on BI (H3), indicating that students with higher ethical awareness are more likely to engage with AI-assisted learning systems [20]. Rather than discouraging adoption, ethical awareness may promote more responsible and informed use of AI technologies [27]. Consistent with PMT, EC also significantly increase PR (H4), confirming that concerns about privacy, bias, transparency, and academic integrity heighten students' perception of AI-related risks [16]. However, PR does not significantly influence BI (H4.1), suggesting that although students recognize potential risks associated with AI systems, these concerns are not strong enough to discourage adoption when the perceived benefits remain high [12]. Similar findings have been reported in recent AI adoption studies where perceived value outweighs potential risks [23]. Taken together, the pattern suggests that students are weighing benefits and drawbacks at the same time and are willing to proceed once the gains look convincing enough to justify the trade-off. The findings demonstrate that students' BI toward AI-assisted learning systems is influenced more strongly by PU and ethical awareness than by trust and PR.

6. CONCLUSION

This research enhances prior research effort on AI implementation in higher education by expanding the PMT and TAM in relation to AI-assisted learning systems. The results validate the critical role of PU in forming students' behavioral and TRUSTIA, reinforcing the relevance of cognitive evaluations in decisions on AI adoption. However, the negative relationship between trust and BI suggests that trust may operate differently in AI-driven educational environments. This finding challenges the conventional assumption that trust invariably promotes adoption and emphasizes the need for future research should examine nuanced and likely effects relating to TRUSTIA systems. Meanwhile, the positive influence of EC on both BI and PR

demonstrates that ethical awareness can function not only as a barrier but also as an enabler of responsible technology adoption. These results emphasize how crucial it is to incorporate ethical and cognitive aspects into future frameworks for AI adoption. The findings offer several practical recommendations. Educators should incorporate AI tools into teaching and learning activities that clearly demonstrate their academic value, such as research assistance, personalized learning support, content creation, and problem-solving exercises, since PU were found to have a significant predictor toward intention AI-assisted educational applications.

Universities should provide structured training programs and orientation sessions that aid students to appreciate the educational benefits and limitations of AI technologies. Given the positive relationship between PU and trust, institutions should promote transparency in AI usage by providing access to reliable and institutionally approved AI platforms. Developers of AI platforms should prioritize user-centered designs that enhance system accuracy and reliability to strengthen students' confidence in AI-generated outputs. The finding of higher trust may lead to more cautious usage further suggests the need to promote critical AI education therefore, institutions should encourage students to evaluate, verify, and critically reflect on AI-generated information rather than relying on AI outputs wholeheartedly. Moreover, institutions need to take up concerns such as algorithmic bias, privacy protection, openness, false information, and academic integrity. Such initiatives can cultivate responsible AI use while helping students develop the required competencies to navigate within AI-driven learning environments. The study further suggests implications for policymakers in education.

The significant association between PR and EC points to the need for institutional standards that foster responsible and ethical usage of AI. Institutions need to develop comprehensive AI governance frameworks that define appropriate AI activities, protect student data privacy, and provide transparency in AI-supported educational processes. Policy makers must set out clear principles for the ethical use of AI tools in education, including standards of fairness, accountability and data protection. Students seem willing to embrace AI technology, even as they identify possible difficulties, and therefore policy interventions should not only seek to minimize danger but also to increase educational value and safeguard users' rights.

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [PD], upon reasonable request.

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