

The influence of affective AI literacy on student satisfaction in higher education

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The Influence of Affective AI Literacy on Student Satisfaction in Higher Education

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Abstract

This study explores the impact of affective AI literacy on student satisfaction in Pakistan's evolving higher education sector, which is placing greater emphasis on sustainable education and market-relevant skills. Technology Acceptance Model together with the Cognitive-Affective Theory of Learning with Media (CATLM) is used as theoretical lens for analyzing this investigation. Conducted across three geographically distinct campuses of COMSATS University Islamabad, the research uses a convenience sampling approach. 237 computer science undergraduates participated through an online survey. Measurement items are adapted from established research to ensure validity and reliability, and the data is analyzed using Structural Equation Modeling (SEM). Results indicate that affective AI literacy positively impacts students' perceptions of AI tools' usefulness ($\beta = 0.655, p < .001$), ease of use ($\beta = 0.613, p < .001$), and satisfaction ($\beta = 0.148, p < .01$). Perceived usefulness and perceived ease of use are found to mediate student satisfaction, enhancing student engagement and personalization in learning. The study urges higher education to include emotional, ethical, and user-friendly AI considerations into curricula, examining how feelings and attitudes shape students' perceptions of AI's usefulness, ease of use, and satisfaction to foster holistic AI literacy. However, limitations include the use of convenience sampling, which focused exclusively on computer science undergraduates from specific campuses, potentially limiting the generalizability to other disciplines or regions. Additionally, future research could explore additional factors like enjoyment, social influence, and academic performance to gain a broader understanding of AI literacy's impact on student satisfaction.

Keywords

Affective AI literacy, Perceived usefulness, Perceived ease of use, Student satisfaction, Technology Acceptance Model, Higher Education Institution

Introduction

In the 21st century, the profound influence of Artificial Intelligence (AI) in various fields is indisputable. The domain of education, being a pivotal sector, is experiencing significant transformations as a result of the incorporation of AI technologies. These innovations incorporate a spectrum of tools such as intelligent tutoring systems and personalized learning environments, fundamentally changing the methods through which educational material is distributed and absorbed. With AI constantly reshaping the educational sphere, it is imperative for educational stakeholders to comprehend the effective adoption of AI technologies [1]. AI literacy, as refers to a set of skills that enable individuals to understand the effective use of AI technologies [2], [3], is increasingly acknowledged as an essential skill that students need to acquire especially within educational environments [4]. This literacy goes beyond mere technical expertise, including a wider range of skills that empower students to engage efficiently with AI technologies [5]. Despite the significant emphasis on the cognitive aspects of AI literacy, such as understanding AI algorithms and data analysis, the affective AI dimensions, which encompass attitudes, emotions, and values, play a crucial yet underexplored role in AI engagement and learning effectiveness [6].

Being a significant subset of AI literacy, affective AI literacy can be comprehensively understood through the ABCE model, comprising Affective, Behavioral, Cognitive, and Ethical dimensions. The multidimensional structure of ABCE model emphasizes the need for learners to not only comprehend how AI tools operates (cognitive), but also understand their appropriate usage behaviors (behavioral), emotional responses (affective) and engaging with AI technologies responsibly (ethical) [7]. Considering this background, Affective AI literacy refers to the emotional and attitudinal elements that play a significant role in shaping how learners perceive and engage with AI technologies. This emotional engagement is particularly pertinent in educational contexts where AI tools are specifically designed to interact with students in customized and dynamic ways. Technology Acceptance Model (TAM) [8], together with the Cognitive-Affective Theory of Learning with Media (CATLM) [9] provides a robust theoretical lens for analyzing the impact of learner's affective states, cognitive processes, and perceptions of technology on learning outcomes. CATLM speculates that when cognitive load is managed, motivation is maintained, and affective engagement is high, this lead towards meaningful learning. Similar factors are also highlighted in TAM's constructs of perceived usefulness and

ease of use. The emotional response has a notable influence on student motivation, acceptance of technology, and, ultimately, the educational outcomes linked to AI utilization [10]. For instance, students with high intrinsic motivation might explore AI applications independently, while those with high self-efficacy are more likely to use AI in complex projects without feeling intimidated. Research indicates that affective factors often act as drivers of the acceptance and use of technology in educational settings, influencing the perceived ease of use and perceived usefulness [11].

Despite the acknowledged significance of affective factors in technology adoption, a notable gap persists in literature. Previous research shows that students' emotional engagement with technology boosts motivation [12], yet the affective dimensions of AI literacy remain critically underexplored within the university context. This oversight hinders the development of a holistic AI literacy framework that addresses all facets of student engagement. While cognitive skills are important, affective AI literacy is crucial for sustained learning. Therefore, this study aims to bridge this gap by examining how affective AI literacy impacts perceived usefulness, perceived ease of use, and student satisfaction in an academic setting [2].

Pakistan's higher education system, with over 200 institutions, is rapidly advancing to integrate modern technologies like AI despite challenges like resource limitations and regional disparities [13]. As AI transforms learning, understanding the affective AI domain becomes essential. Student's attitudes and motivations influence their engagement to AI technologies, impacting learning effectiveness. By focusing on COMSATS University Islamabad, Pakistan, well-known for its integration of AI into educational methodologies across three distinct campuses in different parts of the country, this research provides a valuable insights into how students' emotional and attitudinal reactions to AI impact their practical engagement with the technology. These campuses collectively offer a thorough depiction of the diverse cultural backgrounds in the country, thereby enhancing the richness of the study's data. The outcomes are expected to guide the development of novel approaches in educational policies and curriculum formulation, especially in cultivating favorable emotional and attitudinal orientations towards AI among students.

Therefore, this study aims to address the gap by investigating how affective AI literacy influences students' perceptions and satisfaction within AI-enhanced higher education. Grounded in the Technology Acceptance Model (TAM) and the Cognitive-Affective Theory of Learning

with Media (CATLM), this research examines the emotional and motivational factors shaping learners' acceptance of AI technologies. Accordingly, the study addresses the following research questions:

RQ1: How does affective AI literacy influence students' perceived usefulness of AI technologies?

RQ2: How does affective AI literacy influence students' perceived ease of use of AI technologies?

RQ3: How does affective AI literacy influence student satisfaction in AI-enhanced learning environments?

RQ4: Do perceived usefulness and perceived ease of use mediate the relationship between affective AI literacy and student satisfaction?

This paper proceeds by reviewing the relevant literature, detailing the methodology used to collect and analyse the data, presenting the findings, and finally discussing their implications for theory and practice in higher education.

Literature Review

Theoretical Framework

AI literacy in higher education is an emerging and vital area that focuses on equipping students and educators with the knowledge needed to effectively engage with AI technologies. Research indicates that AI literacy encompasses a range of competencies, from basic understanding of AI concepts to the ability to work with AI systems in complex, ambiguous situations [14], [15]. The development of AI literacy is essential for preparing students to navigate an AI-driven world [16]. It has been conceptualized in various ways, but more recently, the ABCE model has been adopted to provide a multidimensional understanding of AI literacy [5], [7]. This framework comprises four dimensions: *affective* (emotions, motivation, and attitudes toward AI), *behavioral* (practical engagement and use of AI tools), *cognitive* (knowledge and understanding of AI concepts), and *ethical* (responsible and ethical use of AI technologies) [2].

The cognitive dimension refers to students' understanding of AI concepts, principles, and systems the 'what' and 'how' of AI knowledge. The ethical dimension focuses on responsible and fair use of AI, including awareness of issues such as bias and accountability. In contrast, the affective dimension captures the emotional and motivational aspects of AI learning such as

students' interest and willingness to engage with AI technologies. Among these, the affective dimension of AI literacy is critical, focusing on students' emotions, attitudes, and motivation towards AI [17], [18]. It actually refers to a person's innate emotional desire to accept the change. Positive emotions enhance interest and motivation, while negative feelings might hinder learning progress. Core affective elements include intrinsic motivation, self-efficacy, career interest, and confidence, which together influence students' engagement and learning outcomes. Learners who feel capable and curious are more likely to explore AI deeply and participate actively in AI-related activities, creating a reinforcing cycle of motivation and competence [16], [17]. While previous research has primarily focused on the role of affective literacy in shaping technology acceptance, emerging evidence also highlights its influence on academic achievement, as emotional engagement fosters sustained motivation and deeper cognitive processing, leading to improved learning performance [19].

The Cognitive-Affective Theory of Learning with Media (CATLM) [20] explains how learners integrate cognitive and affective processes in multimedia environments. It posits that meaningful learning arises when learners are cognitively engaged through selecting, organizing, and integrating information while also being emotionally supported. In the context of AI literacy, CATLM complements the ABCE framework by highlighting how affective factors sustain engagement and promote conceptual understanding. Moreover, the Technology Acceptance Model (TAM)[8] extends this perspective by explaining how perceived usefulness and ease of use influence learners' willingness to engage with AI tools. Together, CATLM and TAM provide an understanding of how emotional, cognitive, and usability factors shape effective interaction with AI in educational settings [1].

The Technology Acceptance Model (TAM) [8] provides a foundational framework for understanding how individuals accept and adopt technology. It suggests that two beliefs, perceived usefulness and perceived ease of use, shape users' attitudes and behavioral intentions. Recent empirical work in AI education contexts supports the robustness of these constructs: for instance, in a study on ChatGPT adoption among Chinese university students, awareness significantly influenced adoption intention via perceived ease of use, perceived usefulness, and perceived intelligence with trust moderating these relationships [21]. Later extensions of TAM [22] highlight the influence of contextual and emotional factors on these perceptions. Within AI-enabled learning, students' affective AI literacy particularly their motivation, confidence, and curiosity, can enhance perceptions of usefulness and ease of use, thereby increasing their

engagement. In turn, student satisfaction, a key indicator of the quality and sustainability of AI-mediated education [23]. It is further strengthened when these affective and perceptual factors align positively [24], [25]. While this study primarily draws on CATLM and TAM, it also acknowledges insights from Self-Determination Theory [26], which emphasizes the role of intrinsic motivation and perceived competence in sustaining learners' engagement. These motivational perspectives complement CATLM's affective focus and help explain how emotional readiness shapes students' perceptions of AI technologies.

Together, the ABCE model, CATLM, and TAM provide a multi-dimensional understanding of AI literacy, addressing not only the knowledge and ethical aspects (cognitive and ethical), but also the emotional and motivational factors (affective) that influence learners' acceptance and engagement with AI technologies.

Conceptual Framework

This investigation explores the impact of Affective AI Literacy on perceived usefulness, perceived ease of use, and student satisfaction. The proposed conceptual framework (see figure 1) introduces four main hypotheses to study the relationships between affective AI literacy and essential outcome variables.

Perceived usefulness is an individual's assessment of a technology's ability to effectively support or enhance human activities. When users perceive a technology as useful in meeting their needs, their interest and engagement with that technology tend to increase, leading to higher adoption rates and more frequent use [27], [28]. Within the context of AI technologies, affective AI literacy, the combination of students' emotional and motivational readiness to engage with AI, is expected to positively influence their perception of AI's usefulness. When students feel both confident and motivated in their understanding of AI, they are more likely to view these technologies as beneficial tools that can enrich their educational experience and enhance their productivity [29], [30]. Thus, it is hypothesized that students with high levels of affective AI literacy will be better positioned to appreciate the advantages and potential applications of AI, which, in turn, will increase their perceived usefulness of these technologies.

H1: High affective AI literacy leads to higher perceived usefulness.

Perceived ease of use refers to the extent to which individuals believe that a technology will make their activities more manageable and require minimal effort [27]. This perception is an

essential factor that can be significantly shaped by affective AI literacy. Affective AI literacy, which encompasses students' emotional readiness and motivation to engage with AI, influences their self-confidence and perceived ability to use AI technologies effectively. When students possess high level of affective AI literacy, they typically feel more capable and assured in their interactions with AI, which in turn lowers the perceived complexity and effort associated with using these tools [31]. Consequently, students with high affective AI literacy are expected to find AI technologies more intuitive and accessible, as their positive attitudes and motivation help create smoother and more user-friendly experiences with AI systems. Therefore, it is assumed:

H2: High affective AI literacy leads to higher perceived ease of use.

Student satisfaction (SS) represents students' contentment with their learning activities and the services provided, serving as a pivotal factor in determining the quality of education and sustaining engagement in learning [32]. As a critical outcome in educational settings, student satisfaction reflects the degree to which students feel positively about their overall educational experience [33]. When students feel motivated, confident, and competent in their interactions with AI, they are more likely to derive enjoyment from the learning process, thereby enhancing their satisfaction with their education [25]. Thus, it is assumed that high levels of affective AI literacy can contribute significantly to student satisfaction by cultivating positive attitudes and emotional responses towards AI, leading to a more fulfilling and satisfying educational experience.

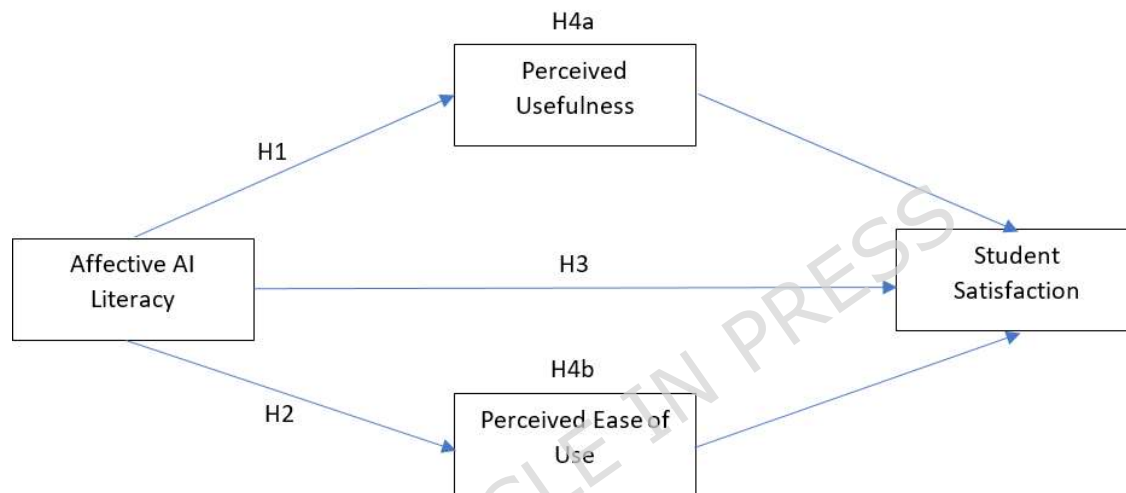
H3: High affective AI literacy leads to higher student satisfaction.

Affective AI literacy may enhance student satisfaction indirectly by positively shaping their perceptions of AI technology's utility. When students possess strong affective AI literacy, they feel more confident, motivated, and emotionally prepared to engage with AI. This readiness allows them to see AI not merely as a tool, but as a valuable asset that can enrich their learning process, improve productivity, and offer practical solutions to educational challenges. As students begin to perceive AI technologies as beneficial and relevant to their learning goals, their overall satisfaction with the educational experience is likely to increase. This positive view fosters a sense of accomplishment, engagement, and enthusiasm toward their studies, ultimately contributing to a more fulfilling and enjoyable learning environment. In this way, affective AI literacy indirectly boosts student satisfaction by making AI technologies appear not only accessible but also impactful and relevant to their educational journey [25]. Therefore, it is

hypothesized that the positive impact of affective AI literacy on student satisfaction is partly explained by its influence on perceived usefulness and perceived ease of use.

H4a: Perceived usefulness mediate the relationship between affective AI literacy and student satisfaction.

H4b: Perceived ease of use mediate the relationship between affective AI literacy and student satisfaction.



Figure#1: Conceptual Framework

Note. Figure created by the author

Materials and Methods

Population

This study focuses on university students with prior AI coursework experience, specifically targeting those from COMSATS University Islamabad (CUI). The reason for selecting CUI is as it is ranked 3rd out of 67 public sector universities of Pakistan [34]. Working with 5 faculties (Engineering, Information Science and Technology, Business Administration and Architecture and Design), CUI has a trend-setting pedagogical approach. CUI's campuses in Abbottabad, Islamabad, and Lahore are selected to ensure a diverse sample representing various cultural backgrounds across the country. The population consists of undergraduate students of computer science department from these three campuses, in their last two semesters who have taken AI courses (Artificial Intelligence, Programming for Artificial Intelligence, Introduction to

Computer Vision, Machine Learning Fundamentals, Natural Language Processing, Artificial Neural Networks and Deep Learning and Knowledge-Based Systems) as part of their degree program. Out of 3,224 students enrolled in the computer science department across these campuses, 613 students fit the target profile for the study.

Sampling

A convenience sampling technique is selected due to the accessibility and proximity of the target student group, enabling efficient data collection. This choice is based on logistical considerations, given the dispersed nature of the campuses and constraints in time and resources. Additionally, convenience sampling facilitated rapid data gathering from students who met the study's criteria of having completed relevant AI courses. This approach aligns with prior research in educational technology, where convenience sampling has been used to obtain targeted insights on digital literacy and AI competencies [35], [36]. Based on a 95% confidence interval, the calculated sample size is 237.

Measurement Instrument

To ensure both validity and reliability, the measurement items for each variable (see Table 1) were carefully adapted from prior research. The scales for each construct were derived from well-established sources and included multiple items designed to capture the essential dimensions of the construct. A standardized five-point Likert scale, ranging from *strongly disagree* (1) to *strongly agree* (5), was employed across all items. These measures were drawn from widely validated instruments frequently used in earlier studies (see Appendix for the complete questionnaire).

For each variable, representative items and sub-dimensions were included to comprehensively capture the construct:

- **Affective AI Literacy** was assessed using ten items adapted from [2]. These items captured key emotional and motivational dimensions, including intrinsic motivation, self-efficacy, career interest in AI, and confidence in AI-related knowledge. For instance, one item measuring intrinsic motivation asked students to indicate their level of agreement with the statement, "*Learning AI is interesting to me.*" Similarly, an item reflecting self-efficacy required students to evaluate the statement, "*I am confident I will perform well on AI-related tasks.*"

- **Perceived Usefulness (PU)** was evaluated using six items adapted from [8],[18]. These items examined the degree to which students perceived AI tools as enhancing their learning effectiveness and overall productivity. For example, one representative item stated, *“Using AI tools improves my learning performance.”*
- **Perceived Ease of Use (PEU)** was measured with 6 items adapted from [8], [18], evaluating how easy and free of effort students perceive AI tools to be. A sample item is *“Learning to operate AI tools is easy for me.”*
- **Student Satisfaction (SS)** was measured with 5 items adapted from [37], [32], reflecting overall contentment with AI-enhanced learning experiences. For instance, *“Overall, I am satisfied with the AI tools used in my courses”* is an item indicating general satisfaction with AI in the learning process.

All items were scored on a 5-point Likert agreement scale (1 = strongly disagree, 5 = strongly agree). The survey instrument was initially drafted and reviewed by two faculty members for clarity and relevance. Minor wording adjustments were made based on their feedback to ensure that the questions were interpreted consistently by participants.

Table 1
Measurement Instrument

Variables	Source	Items
Affective AI literacy	[2]	10 items
Perceived Usefulness	[8]	6 items
Perceived Ease of Use	[8]	6 items
Student Satisfaction	[37]	5 items
Total		27 items

Data Collection & Analysis Techniques

The questionnaire was distributed to students through their course instructors, using both physical paper forms and digital links (emailed and shared via WhatsApp groups). Participation was voluntary, and respondents were assured of anonymity and that their answers would be used

for research purposes only. Regular reminders were sent to maximize response rates. In total, 237 complete questionnaires were collected, yielding the final sample for analysis.

For data analysis, we employed structural equation modeling (SEM) using a combination of SPSS (for preliminary analyses) and SmartPLS 4 (for PLS-SEM path modeling). The analysis procedure included descriptive statistics (frequency distributions, measures of central tendency and dispersion), preliminary checks (correlations and factor analysis), assessment of measurement model quality (reliability and validity analyses), and evaluation of the structural model for hypothesis testing and mediation analysis. Before conducting SEM, we examined the data for adherence to key assumptions:

- **Normality:** Data normality was assessed via skewness and kurtosis for each construct (see Table 3). Some constructs showed skewness values exceeding ± 1 (e.g., skewness for PU = -1.473), indicating moderate departures from normality. Given these deviations and the sample size, a PLS-SEM approach was chosen for the structural model, as PLS is robust to non-normal data distributions. In addition, non-parametric bootstrapping (5000 resamples) was applied in SmartPLS to derive stable standard errors and significance levels, mitigating concerns about non-normality in hypothesis testing.
- **Multicollinearity:** We checked for multicollinearity among the predictor constructs by calculating variance inflation factors (VIFs) for the structural model. All VIF values were well below the common threshold of 5 [34], with most below 3, indicating that multicollinearity was not a concern in our model. This suggests that affective AI literacy, perceived usefulness, and perceived ease of use each contributed distinct information without excessive overlap.
- **Sample Size and Model Complexity:** With $N = 237$, our sample met recommended guidelines for PLS-SEM analysis and was adequate given the model complexity (four constructs, with sufficient indicator loadings). The ratio of observations to indicators was well above the minimum needed for reliable SEM estimation.

All statistical analyses were performed at a 95% confidence level ($\alpha = 0.05$). The analysis proceeded in two stages: first, the **measurement model** was assessed to establish the reliability and validity of the constructs; subsequently, the **structural model** was tested to examine the proposed hypotheses. In addition, model fit indices and explanatory power (R^2 values) were reported to evaluate the adequacy of the model in representing the data.

Ethical Considerations

This study was conducted in accordance with established ethical standards for research with human participants. Prior to data collection, the research protocol was reviewed and approved by the Academic Research Committee at COMSATS University Islamabad (the institutional review board). Participants were fully informed of the study's objectives and the nature of their involvement prior to providing consent. Participation was entirely voluntary, and informed consent was obtained from each participant (implicitly via survey instructions and an opening consent statement) before they proceeded to the questionnaire. Participants were assured of the confidentiality of their responses; no personally identifying information (aside from basic demographics such as age and gender) was collected, and results have been reported in aggregate form only. Throughout the study, we adhered to ethical guidelines as per the Declaration of Helsinki and the policies of the host institutions, ensuring that respondents could withdraw at any time and that no harm would come to them as a result of their participation.

Results

Respondent's Profile & Descriptive Statistics

Variable	N (237)	%
Gender		
Male	177	74.6
Female	60	25.4
Age		
18-24	223	94
25-34	14	6

Table 2

Respondent's Demographic

A total of 237 students completed the survey. The demographic profile of respondents is summarized in Table 2. The sample consisted of 74.6% male and 25.4% female students. The vast majority of respondents (94%) were between 18–24 years old (typical age for senior undergraduates), with a small proportion (6%) between 25–34 years. All participants were computer science majors in their final year of study, with prior exposure to AI-related coursework as described earlier.

Table 3 presents the descriptive statistics for the key constructs, including the mean, standard deviation (SD), skewness, and kurtosis for each composite construct (computed as the average of its item scores). The mean scores for all constructs were moderately high (ranging roughly from 3.83 to 4.07 on a 5-point scale), indicating generally positive perceptions among students. Perceived usefulness (mean \approx 4.07) was slightly higher on average than perceived ease of use (4.00) and student satisfaction (3.86). Affective AI literacy also had a relatively high mean (3.83), suggesting that students felt reasonably confident and motivated regarding AI.

All constructs showed negative skewness (skewness values between -1.137 and -1.473), indicating a left-tail distribution where respondents tended to agree rather than disagree with positive statements about AI. The kurtosis values (1.325 to 1.839) suggest slight to moderate peakedness. While these statistics depart somewhat from a normal distribution (as noted in the Methods), they are within ranges that PLS-SEM can accommodate. No extreme outliers were detected in the data.

	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AI	3.83	.864	-1.253	.158	1.325	.315
PU	4.07	.991	-1.473	.158	1.834	.315
PEU	4.00	.974	-1.390	.158	1.839	.315
SS	3.86	.919	-1.137	.158	1.543	.315

Table 3

Descriptive Statistics

Note: AI = Artificial Intelligence, PU = Perceived Usefulness, PEU = Perceived Ease of Use, SS = Student Satisfaction

Correlation Analysis

PEU ($r = 0.613$, $p < 0.01$), PU ($r = 0.655$, $p < 0.01$), and SS ($r = 0.604$, $p < 0.01$) all show a positive correlation with AI, suggesting that AI positively influences student satisfaction, driven by its perceived ease of use and perceived usefulness in education (see table 4). A strong positive correlation indicates that respondents who perceive ease of use favorably also place a high value on perceived usefulness ($r = 0.728$, $p < 0.01$) and student satisfaction ($r = 0.754$, $p < 0.01$). The results show that student satisfaction is highly related to the perceived usefulness ($r = 0.691$, $p < 0.01$).

	AI	PEU	PU	SS
AI				
PEU	0.613**			
PU	0.655**	0.728**		
SS	0.604**	0.754**	0.691**	

Table 4

Correlation

Note: **. Correlation is significant at the 0.01 level (2-tailed).

AI (Artificial Intelligence), PU (Perceived Usefulness), PEU (Perceived Ease of Use),

SS = Student Satisfaction

Measurement Model

The study uses a factor analysis to identify the latent components that influence respondents' opinions of AI, such as Perceived Usefulness (PU), Perceived Ease of Use (PEU) and its impact on Student Satisfaction (SS) (See table 5). The study evaluates the reliability and validity of the measurement instruments by calculating Cronbach's alpha, composite reliability, and average variance extracted (AVE) for the constructs. Cronbach's alpha values ranged from 0.872 to 0.908, suggesting that the internal consistency for the constructs is satisfactory. The composite reliability values shows consistent patterns, varying between 0.921 and 0.936 [38]. These results indicate that the dependability is satisfactory, as values over the recommended threshold of 0.70 indicate that the measurement instruments are dependable. In addition, the average variance extracted values, which ranged from 0.596 to 0.829, indicated that the constructs were able to explain a significant amount of their own variability [38]. This finding supports the idea that the constructs have convergent validity. Overall, the evaluations of reliability and validity instill trust

in the strength and accuracy of the measurement equipment used in the study, hence bolstering the legitimacy of the research findings.

Table 5
Measurement Model

Variables	Indicators	Factor loadings	Cronbach's Alpha	Composite Reliability	AVE
AI	Q1	0.695	0.903	0.922	0.596
	Q2	0.831			
	Q3	0.777			
	Q4	0.839			
	Q5	0.783			
	Q6	0.780			
	Q7	0.718			
	Q8	0.742			
PU	Q9	0.915	0.897	0.936	0.829
	Q10	0.888			
	Q11	0.911			
	Q12	0.828			
PEU	Q13	0.913	0.908	0.936	0.785
	Q14	0.930			
	Q15	0.888			
SS	Q16	0.903	0.872	0.921	0.796
	Q17	0.914			
	Q18	0.859			

AI = Artificial Intelligence, PU = Perceived Usefulness, PEU = Perceived Ease of Use, SS = Student Satisfaction

Discriminant Validity

It is noteworthy that all construct pairs had HTMT ratios below the widely accepted cutoff of 0.85, indicating respectable discriminant validity [39]. As an illustration, the HTMT ratios of 0.665, 0.708 and 0.664 are found between AI and PEU, PU and SS respectively. Collectively, these findings confirm that the study's constructs are unique from one another and give confidence that the measurement model accurately reflects the distinctive features of each underlying construct, supporting the measurement model's discriminant validity (See table 6).

AI

PEU

PU

SS

AI			
PEU	0.665		
PU	0.708	0.806	
SS	0.664	0.851	0.772

Table 6

Heterotrait-Monotrait Ratio (HTMT)

AI = Artificial Intelligence, PU = Perceived Usefulness, PEU = Perceived Ease of Use, SS = Student Satisfaction

Model Fit

Although PLS-SEM is primarily focused on prediction and does not produce the same array of global fit indices as covariance-based SEM, we report here the model fit indices available for our PLS path model (see Table 7). We considered the Standardized Root Mean Square Residual (SRMR) as a measure of approximate model fit. For the saturated model (which considers the correlations between all constructs), SRMR = 0.076, which is below the 0.08 threshold commonly considered a good fit [35]. For the estimated model (the structural model with the specified paths), SRMR was 0.109, which is slightly above the desired range, suggesting the structural model has a bit more residual discrepancy. Other fit metrics provided include the d_{ULS} (the squared Euclidean distance; 0.999 for saturated vs 2.017 for estimated) and d_G (the geodesic distance; 0.481 vs 0.551), with lower values indicating better fit (thus the saturated model again shows smaller discrepancy values than the estimated model). The Chi-square of the model implied matrix was 671.475 (saturated) vs 707.251 (estimated), and the Normed Fit Index (NFI) was 0.806 for the saturated model and 0.796 for the estimated model. Overall, the saturated model (which corresponds closely to the measurement model) shows a slightly better fit than the final structural model. Nevertheless, the differences are not large, and the SRMR of the estimated model being around 0.109 indicates a somewhat acceptable fit given the complexity of the model and PLS's focus on prediction. In sum, the model's fit indices suggest that the model explains the data reasonably well, though there may be minor areas for improvement. Importantly, the model explains a substantial portion of variance in key outcomes (as discussed below), supporting its usefulness even if some fit indices are marginal.

Table 7

Model Fit

	Saturated model	Estimated model
SRMR	0.076	0.109
d_ULS	0.999	2.017
d_G	0.481	0.551
Chi-square	671.475	707.251
NFI	0.806	0.796

Note: The saturated model considers all constructs freely correlated, whereas the estimated model uses the theorized paths. An SRMR below 0.08 is considered a good fit [35]. NFI values range 0–1 (higher is better).

In addition to these fit indices, we also report the model's explanatory power. The structural model's R^2 values indicate the proportion of variance explained in each endogenous construct: Affective AI literacy (being exogenous) has no R^2 , whereas perceived usefulness had $R^2 \approx 0.43$ (indicating 43% of the variance in PU is explained by affective AI literacy), perceived ease of use had $R^2 \approx 0.38$ (38% variance explained by affective AI literacy), and student satisfaction had $R^2 \approx 0.62$. In other words, about 62% of the variance in student satisfaction is jointly explained by affective AI literacy, perceived usefulness, and perceived ease of use in our model. This is a substantial amount of explained variance for behavioral research, suggesting the model has strong explanatory capability for student satisfaction in the context of AI-enhanced education.

Hypotheses Testing

The path coefficients and their significance levels are shown in Table 8. All three direct hypotheses (H1, H2, H3) were supported by the data:

- H1: Affective AI Literacy \rightarrow Perceived Usefulness, $\beta = 0.655$, $p < .001$. This path coefficient is positive and significant, indicating that higher affective AI literacy is associated with higher perceived usefulness of AI tools. Students who are more emotionally and motivationally engaged with AI tend to perceive AI technologies as more useful in their studies, supporting H1.
- H2: Affective AI Literacy \rightarrow Perceived Ease of Use, $\beta = 0.613$, $p < .001$. This result shows that affective AI literacy has a significant positive effect on how easy students perceive AI tools to be. In other words, students who are more comfortable and enthusiastic about AI report less difficulty in using AI applications, confirming H2.
- H3: Affective AI Literacy \rightarrow Student Satisfaction, $\beta = 0.148$, $p = .005$ (which is $< .01$). This indicates a positive direct effect of affective AI literacy on student satisfaction.

While significant, this direct effect is relatively modest in magnitude ($\beta \approx 0.15$) compared to H1 and H2. This suggests that affective AI literacy on its own has a positive but limited direct influence on satisfaction, pointing to the potential importance of indirect pathways (which we examine under mediation).

	Path Coefficient	P values	Result
AI -> PU	0.655	0.000	Supported H1
AI -> PEU	0.613	0.000	Supported H2
AI -> SS	0.148	0.005	Supported H3

Table 8

Path coefficients

AI = Artificial Intelligence, PU = Perceived Usefulness, EOU = Perceived Ease of Use, SS = Student Satisfaction

Mediation Analysis

To test the mediation hypotheses H4a and H4b, we examined the indirect effects of affective AI literacy on student satisfaction through perceived usefulness and through perceived ease of use, respectively.

- Mediation via Perceived Usefulness (H4a): Affective AI literacy had a strong positive effect on perceived usefulness ($a = 0.655^{***}$), and perceived usefulness in turn had a significant positive effect on student satisfaction ($b = 0.236^{**}$, $p < .01$). The product of these (the indirect effect $a \times b$) was $\beta_{\text{indirect}} = 0.155$ (approximately), which was statistically significant ($p < .01$). Meanwhile, with PU in the model, the direct effect of affective AI literacy on satisfaction (c') was 0.148^{**} and remained significant. These results indicate partial mediation – perceived usefulness carries a portion of the effect of AI literacy to satisfaction, supporting H4a. In practical terms, affective AI literacy improves student satisfaction in part because it increases students' perceptions of AI's usefulness, although some direct effect of AI literacy on satisfaction persists independent of usefulness.
- Mediation via Perceived Ease of Use (H4b): Similarly, affective AI literacy significantly influenced perceived ease of use ($a = 0.613^{***}$), and perceived ease of use significantly influenced student satisfaction ($b = 0.492^{***}$, $p < .001$). The indirect effect through PEU was $\beta_{\text{indirect}} = 0.301$ (significant at $p < .001$). In the presence of PEU, the direct effect of AI literacy on satisfaction (c') was again 0.148^{**} . This confirms partial mediation for

H4b as well. The mediated pathway via perceived ease of use is notably stronger than that via perceived usefulness, given the larger coefficient (0.301 vs 0.155). The fact that the direct effect remains significant in both cases (and the model including both mediators still showed a direct effect of 0.148**) indicates that neither mediator alone fully accounts for the influence of affective AI literacy on satisfaction – rather, both mediators jointly transmit a substantial portion of the effect, with perceived ease of use playing a particularly impactful role.

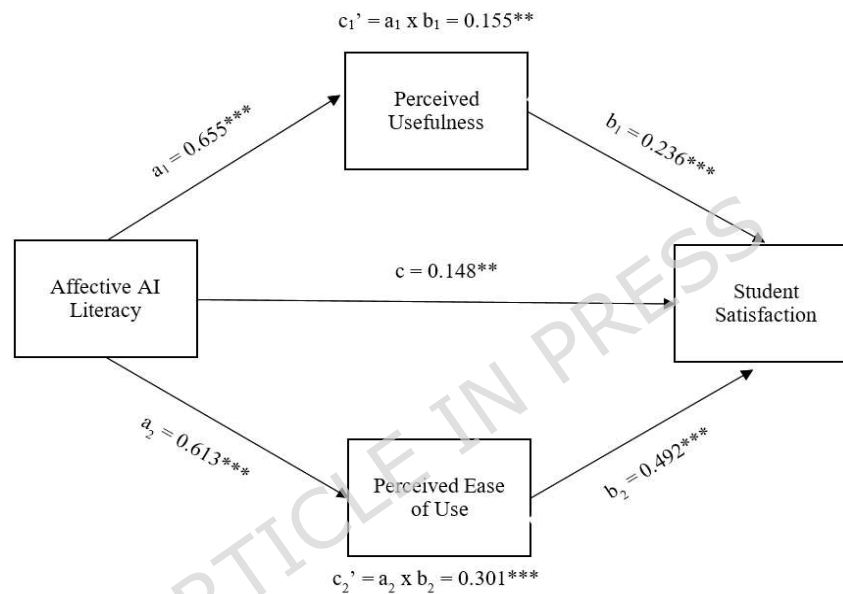
Taken together, the mediation analysis highlights that perceived ease of use (PEU) is a particularly strong mediator between affective AI literacy and satisfaction. The indirect effect via PEU ($\beta = 0.301$) is roughly double the direct effect (0.148) of AI literacy on satisfaction, underscoring that a large part of why affective AI literacy leads to satisfaction is because more affectively engaged students find the tools easier to use. The indirect effect via perceived usefulness, while significant, is more modest ($\beta \approx 0.155$). Both mediators combined account for a substantial enhancement of the impact of AI literacy on satisfaction (and as noted earlier, about 62% of the variance in satisfaction is explained by the model including these mediators). Importantly, because the direct effect remains positive and significant, we infer that affective AI literacy influences student satisfaction both directly and indirectly, with partial mediation through TAM constructs rather than full mediation.

Path	Paths coefficients		Specific Indirect effect	Direct effect	Result	Comment
	a	b	ab	c		
AI → SS						
AI → PU → SS	0.655***	0.236***	0.155**	0.148 **	Supported H4a	Partial mediation
AI → PEU → SS	0.613***	0.492***	0.301***		Supported H4b	Partial mediation

Table 9

Results for Mediation

AI =Artificial Intelligence, PU =Perceived Usefulness, EOU = Perceived Ease of Use, SS = Student Satisfaction *Note: *p < .05, **p < 0.01, ***p < .001.*



Note: ***, *, * on paths denote significance at the .001, .01, and .05 levels, respectively. Direct effect (c) is the effect of AI on SS when the mediator is included in the model. Both H4a and H4b are supported, indicating that PU and PEU each partially mediate the effect of affective AI literacy on satisfaction. Figure created by the author

Figure# 2: Structural Model (Path coefficient and p values)

Note. Figure created by the author

Discussion

AI literacy is a leading trend in the education sector and recognized as an essential skill increasingly expected of students. Among the four main areas of AI literacy, Affective AI literacy is particularly important, as it encompasses students' natural emotional and motivational responses to a subject [40]. Accordingly, the focus of this study is to investigate the impact of

Affective AI literacy on perceived usefulness, perceived ease of use, and student satisfaction. The findings indicate a significant positive relationship (path coefficient= 0.655***) between affective AI literacy and perceived usefulness. When students score high on the affective aspect of AI literacy, which includes their emotional and motivational readiness to engage with AI, they are more likely to perceive AI as useful. Perceived usefulness refers to a user's belief in a technology's ability to provide assistance in different tasks and enhance productivity. This represents an individual's evaluation of how well a technology can improve or streamline human activities [27], [28]. When users see a technology as beneficial in meeting their needs, their interest and engagement with that technology tend to grow, leading to higher adoption rates and more frequent use. In the context of AI, affective AI literacy (including students' emotional confidence and intrinsic motivation to use AI) is expected to strengthen the user's perception of AI's value. Students who feel confident in comprehending the use of AI tools, and at the same time they feel motivated, are more inclined to view it as a valuable tool. AI becomes a dynamic partner in their education, helping them manage tasks more efficiently, gain deeper insights, and access customized learning materials. Consequently, this positive viewpoint promotes a deeper integration of AI into their daily academic practices, resulting in improved productivity, greater engagement and enrich learning experiences [41].

The results of the present research also demonstrated a significant positive association (0.613***) between AI literacy and perceived ease of use, which refers to the extent to which users anticipate using new technology with minimal difficulty [41]. Studies have already shown that AI literacy contributes to a sense of empowerment and autonomy among users, which in turn raises their perceived ease of use [42], [43]. When students have a high level of affective AI literacy, they are more likely to possess a strong motivation, confidence, interest, and self-efficacy in using AI technology. This literacy equips them with not only the technical skills but also the emotional and cognitive readiness to engage meaningfully with AI tools. Consequently, students who feel capable and knowledgeable about AI are less likely to experience pressure or nervousness around AI technologies, which can otherwise be a significant barrier to use. The sense of competence that comes with affective literacy creates a positive perception of AI's ease of use, making the technology seem accessible and beneficial to their personal learning or productivity goals. This positive attitude also leads to reduces user resistance, a common challenge in technology adoption, since students with high AI literacy are less likely to view AI systems as overly complex. Instead, they recognize the utility of these tools and approach them

as resources that enhance their capabilities rather than detract from them. Research supports that individuals with a strong sense of self-efficacy and affective technological literacy are tend to involve positively with digital tools, considering them easier to use and incorporating them more readily into their daily activities. As a result, their productivity and learning increase substantially [42], [43].

Student satisfaction (SS) plays a major role in shaping the quality of education and preserving the aspect of learning [32]. The current investigation has established a significant positive relationship (0.148**) between affective AI literacy and student satisfaction. When students possess a high level of AI literacy, they are more comfortable and enthusiastic about interacting with AI technologies, which enhances their engagement and satisfaction with these tools. High affective AI literacy tends to promote engagement, and confidence in using AI tools, leading to a more enjoyable and satisfying educational experience. For example, a well-developed understanding with AI have been shown to reduce technology-related anxiety and promote positive attitudes, which in turn increase academic motivation and satisfaction. Moreover, when students can confidently engage with AI tools, they experience enhanced academic well-being, which has been positively linked to educational outcomes and personal satisfaction [44],[19]. Additionally, when students are motivated and self-assured in using AI, they are more likely to explore its features fully, discovering the ways in which AI may streamline their work, personalize their learning, and make studying more effective. Research suggests that such positive experiences with technology usage contribute to heightened satisfaction, as students feel their needs and expectations are met, and they experience fewer frustrations or challenges [8]. Eventually, when students feel confident in their AI literacy, they not only adopt AI tools quickly but also derive more value from them, leading to greater satisfaction and enhanced learning experiences.

The findings indicate that while there is a positive relationship between affective AI literacy and student satisfaction, introducing perceived ease of use and perceived usefulness as mediators significantly strengthens this impact. Particularly, perceived ease of use acts as a strong mediator (0.301***) between affective AI literacy and student satisfaction. A strong mediation of perceived ease of use between affective AI literacy and student satisfaction underscores the fundamental role of user-friendliness in the educational experience with AI-driven tools. Affective AI literacy involves understanding and effectively using AI by incorporating emotions, leads to enhanced students' ability to engage positively with educational technology. However, if

these AI tools are perceived as challenging to use, this may not directly guide to increased satisfaction. When students perceive these tools as easy to use, it bridges the gap between literacy and satisfaction, allowing them to feel competent and empowered while interacting with AI in learning environments. Consequently, perceived ease of use can significantly enhance the positive effects of affective AI literacy on student satisfaction, highlighting its importance as a mediator in educational technology adoption [45], [46]. Moreover, studies applying the Technology Acceptance Model (TAM) show that students' perceptions of usability directly affect their willingness to engage with AI in learning, indicating that ease of use amplifies the positive effects of AI literacy on satisfaction and motivation to adopt new tools [47]. Incorporating AI tools which are easy to use in educational settings can help in optimizing the benefits of AI literacy, assisting learners to feel more confident in their tech interactions. While perceived ease of use plays a stronger mediating role, perceived usefulness also significantly enhances the relationship (0.155**) between affective AI literacy and student satisfaction. Student's satisfaction with AI tools increases when they find these tools helpful in achieving their educational goals, although not impacting as highly as perceived ease of use does. This suggests that while perceived ease of use primarily facilitates the comfort and accessibility of AI tools, perceived usefulness contributes by assuring students of the tool's value in supporting their learning objectives [47]. Together, these factors underscore the importance of both intuitive design and clear utility in promoting satisfaction with AI in education [48].

Furthermore, these conclusions are also supported by the Cognitive Affective Theory of Learning with Media (CATLM), which signifies the relationship between cognitive and affective processes in multimedia learning environments. This theory suggests that when learners are emotionally involved with the technology and find these tools beneficial and easy to use, their meaningful learning outcomes enhances along with increased motivation and reduced cognitive load. Affective AI literacy, by enhancing emotional readiness and motivation, stimulates these areas. Ease of use lessens unnecessary cognitive effort, helping students to focus on meaningful learning tasks. Perceived usefulness contributes by reinforcing the instrumental value of AI in achieving learning outcomes, completing the motivational loop. Hence, incorporating easy to use and pedagogically meaningful AI tools can enhance the benefits of affective AI literacy. Collectively, insights from both TAM and CATLM highlight the importance of designing AI-driven educational technologies that are not only functionally effective but also emotionally intuitive, in order to maximize student satisfaction and academic success [48].

Conclusion

Affective AI literacy has the capability to considerably increase student satisfaction and learning outcomes generally. By providing learners with the skills to comprehend and interact effectively with emotionally responsive AI, affective AI literacy facilitates them to benefit from technology that will be supportive of their learning needs. This literacy fosters a perception of AI tools as both beneficial and easy to use, which directly influences satisfaction by making learning more engaging and tailored to their needs. Students who feel competent in using AI-driven educational tools experience a smoother, more enjoyable learning process, ultimately reducing frustrations and promoting a positive attitude toward learning technology, which in return leads to enhanced learning performance [19].

Implications of the Study

This study's findings have significant implications, especially for higher education in developing countries like Pakistan. The results show how crucial it is to include emotional factors like motivation, confidence, and ethical awareness when designing AI courses. Doing this helps create learning experiences that feel more engaging and personalized, making students more satisfied and ready to embrace AI technology. It also points to the need for easy-to-use educational tools that connect with both the feelings and thinking of students. Educators may boost the perceived usefulness of AI by designing such learning experiences that clearly demonstrate its applications in real-world, for instance through the use of AI-powered writing tools etc. Furthermore, it is also important to adopt user-friendly AI tools, which will provide students opportunity to engage and implement these tools easily and quickly. Additionally, offering hands-on workshops or tutorials can boost student confidence and highlight the practical benefits of these tools. Reflective assignments that explore how AI interprets and responds to human emotions may also help in this regard. Implementing AI use step by step by aligning tool selection with students' digital competencies, educators can effectively promote affective AI literacy, consequently enhancing student satisfaction and engagement in higher education. On a social level, helping students develop emotional awareness around AI can lead to more inclusive and thoughtful use of technology. It encourages people to use AI in ways that respect different cultures and values. In countries facing resource constraints and rapid digital transformation,

such an approach is vital for ensuring equitable access to AI education and preparing students to navigate the ethical challenges of emerging technologies.

Limitations

Like all empirical research, this study has certain limitations that must be considered when interpreting the findings. First, the use of a convenience sample consisting solely of undergraduate computer science students from three campuses of a single Pakistani university constrains the generalizability of results. The homogeneity of the sample, both in terms of discipline and institution, limits external validity across other academic fields, institutions, and cultural contexts. Moreover, since participants had prior exposure to AI coursework, their baseline knowledge and interest may have been higher than average. This may have biased results toward more favorable perceptions, particularly regarding perceived usefulness and ease of use, thus potentially amplifying the observed associations with affective AI literacy. Future studies should therefore include more diverse student populations, spanning multiple disciplines, institutions, and regions, to validate and extend these findings.

Secondly, reliance on self-reported survey data introduces potential biases, including social desirability and inaccuracies in self-assessment. Although anonymity was assured, some degree of over-reporting positive attitudes cannot be ruled out. To mitigate these concerns, future research should incorporate complementary methods such as objective usage data, performance records, or mixed-methods approaches (e.g., interviews, focus groups). Such triangulation would enrich understanding by capturing both the measurable and nuanced aspects of students' emotional engagement with AI, thereby enhancing reliability and reducing common method bias. Furthermore, the study's cross-sectional design captures only a single point in time, limiting causal inference. While the identified relationships are theoretically grounded and supported by SEM analysis, causality cannot be assumed. Longitudinal or experimental designs would be valuable in determining whether, for example, targeted interventions to improve affective AI literacy subsequently enhance student satisfaction, or whether simplifying tool usability increases affective engagement over time.

Finally, the study examined a limited set of variables. Although perceived usefulness and ease of use were included as mediators, other potentially relevant factors such as enjoyment, self-regulation, social influence, technological anxiety, or learning autonomy were not addressed. Incorporating these variables in future research could provide a more comprehensive

understanding of the mechanisms through which affective AI literacy shapes student satisfaction. In sum, while this study offers important insights into the role of affective AI literacy in shaping technology acceptance and satisfaction, its contributions should be interpreted in light of these methodological and conceptual limitations.

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Declarations

Availability of data and materials

The anonymised dataset supporting the findings of this study is available as supplementary material with this article. All identifiable personal information has been removed to ensure participant confidentiality and compliance with data protection regulations.

Competing interests

There were no competing interests among the participants during the course of this research.

Funding

There was no funding received for carrying out this research.

Consent to publish

Not Applicable

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Clinical trial number

Not applicable

Ethics approval

This study was reviewed and approved by the Academic Research Committee at COMSATS University Islamabad. All procedures involving human participants were in accordance with ethical standards, and informed consent was obtained from all participants.

Consent to Participate

Informed consent has been taken from all participants in the study.

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Appendix

AI literacy -Questionnaire

Scale: 5- point scale ranging from ‘strongly disagree’ (1) to ‘strongly agree’ (5).

1. **Name (Optional):** _____
2. **Gender:** ρ Male ρ Female
3. **Age:** ρ18-24 years ρ25-34years ρ35-44 years ρ45 and above

Affective learning*Intrinsic motivation*

1. Artificial intelligence is relevant to my everyday life (e.g., personal, work).
2. Learning AI is interesting.
3. Learning AI makes my everyday life more meaningful.
4. I am curious about discovering new AI technologies.

Self-efficacy

1. I am confident I will perform well on AI related tasks.
2. I am confident I will do well on AI related projects.
3. I believe I can master AI knowledge and skills.
4. I believe I can earn good grades in AI related assessments.

Perceived Usefulness

1. Using AI tools will improve my learning.
2. Using AI tools will enhance my effectiveness.
3. I find AI tools a useful tool in my learning.
4. Using AI tools will save my time.

Perceived Ease of use

1. I find AI tools easy to use.
2. My interaction with AI tools is clear and understandable.
3. I find it easy to get AI tools to do what I want it to do.

Student satisfaction

1. I am pleased enough with AI tools.

2. AI tools satisfies my educational needs.
3. I am satisfied with the performance of AI tools.

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