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Personalization Imperative: Unpacking Student-AI Relationships Through a Mixed-Methods Lens in Indonesian Higher Education

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Abstract. While extensive research has examined the technical effectiveness of artificial intelligence (AI) in improving learning outcomes, limited attention has been paid to students' perspectives as primary users, particularly within culturally specific contexts such as developing countries. Moreover, the mechanisms through which AI influences student satisfaction and sustained adoption remain insufficiently theorized, especially regarding the interplay between effectiveness and personalization. This study investigated AI effectiveness in improving students' learning outcomes, its influence on students' personalization, and challenges and experiences with AI as their learning companion. Employing a sequential exploratory mixed-methods design, 85 mathematics education students were surveyed at Universitas Terbuka, Indonesia, followed by qualitative thematic analysis of open-ended responses. The multiple regression analysis revealed an intriguing paradox, indicating that AI personalization is the only significant predictor of both satisfaction and intention to continue using AI tools (β = 0.450, p < 0.05), explaining 32.8% of variance. Despite showing a significant positive correlation in the bivariate analysis, AI effectiveness did not significantly predict satisfaction and continued intention. Concerns exhibited no meaningful influence on adoption intentions. Analysis of qualitative data uncovered three superordinate themes: (1) ambivalent experiences characterized by operational efficiency yet informational inaccuracy, with 73.5% of students developing adaptive verification strategies; (2) dual influences on collaboration, where AI facilitated communication (25.9%) yet inhibited peer interaction (35.3%); and (3) systemic challenges spanning

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epistemological (32.9%), pedagogical (29.4%), and social (21.2%) dimensions. The findings imply that adaptive personalization is essential for converting the general effectiveness of AI into meaningful, context-specific value for learners, emphasizing that educational technologies must prioritize personalization to enhance engagement and support sustainable adoption in diverse learning settings. This study contributes to technology adoption theory by demonstrating that personalization acts as a key mediator, challenging traditional technology acceptance model assumptions. The study offers empirical insights into the role of personalized AI in Indonesian higher education, informing the design of more culturally responsive and effective educational technologies.

Keywords: artificial intelligence; personalization; student satisfaction; technology acceptance; higher education; mixed methods

1. Introduction

Artificial intelligence (AI) is rapidly transforming various sectors, including education, where it offers new possibilities to improve learning experiences. The adoption of AI technology in education has been steadily increasing, creating opportunities to enhance efficiency, accessibility, and the quality of student learning. This progress is particularly evident through tools such as ChatGPT, interactive quiz platforms, and adaptive learning systems capable of providing real-time feedback (Jahani et al., 2024; Joel et al., 2024; Monike et al., 2025; Ningsih, 2025; Sholeh, 2025; Yadav, 2024). The use of these technologies enables students to access learning resources flexibly and adjust their learning pace according to individual needs (Duarte et al., 2025; Morgado et al., 2025; Sudirman et al., 2025).

In particular, ChatGPT significantly enriches education by offering dynamic, personalized learning experiences and real-time feedback, thereby boosting teaching efficiency and learner engagement (Alam, 2023). However, the integration of AI into higher education still faces various challenges, including the risk of over-reliance, which may negatively impact students' academic autonomy (Doğan et al., 2025; Wei & Wei, 2025). While systematic reviews indicate that AI tools such as ChatGPT clearly contribute to educational efficiency, their impact on student engagement tends to be conditional, being strongly influenced by instructional design, learning context, and students' digital literacy levels. In well-structured learning environments, AI has been shown to support deeper engagement by offering personalized feedback, interactive dialogue, and adaptive learning pathways (Salih et al., 2025).

Early findings from a survey conducted with 86 students enrolled in the mathematics education program at Universitas Terbuka highlighted an interesting contradiction: while a majority of students (67%) actively use AI technologies such as ChatGPT and Quizizz to access additional learning materials, enhance problem-solving skills, and boost their study efficiency, this adoption occurs within the unique context of Indonesian higher education, where digital literacy and resource accessibility vary widely. However, the same proportion of students also indicated experiencing significant challenges, including excessive dependence on technology, errors or inaccuracies in outputs

– particularly in mathematical calculations – and difficulties in evaluating the validity of information generated by AI. These findings highlight a tangible gap between the potential of AI as an innovative learning tool and the realities of its implementation in Indonesian higher education. This phenomenon suggests that although AI can accelerate access to information and support learning processes, its use in the absence of adequate guidance and digital literacy may diminish students' academic autonomy and critical thinking skills. Students tend to rely on AI outputs without critical evaluation, thereby reducing opportunities for independent reasoning, metacognitive regulation, and reflective judgment.

In addition, several studies have explored the integration of AI into higher education from various perspectives. Almheiri et al. (2025) demonstrated that AI tutoring systems can enhance student learning outcomes through personalized content and an adaptive learning pace. Similarly, Ali and Abdel-Haq (2021) identified four key areas of AI application in higher education: student profiling and prediction, intelligent tutoring systems, assessment and evaluation, as well as adaptive support and personalized learning. More recent empirical studies have provided further insights. For instance, Ravšelj et al. (2025) revealed that students use ChatGPT for brainstorming, text summarization, and searching for research articles. Abbas et al. (2024), in a longitudinal study, found that when students face higher academic workload and time pressure, they tend to rely more heavily on ChatGPT.

Likewise, Gasaymeh et al. (2025) reported a high prevalence of ChatGPT use for both academic and personal purposes. Furthermore, empirical research by Awad and Oueida (2024) highlights that while AI provides substantial benefits, such as personalized learning, improved educational outcomes, and enhanced student engagement, it also poses challenges, including over-reliance on technology, diminished critical thinking, and the risk of academic dishonesty. In the context of student perceptions, Chan and Hu (2023), in a survey of undergraduate and postgraduate students across disciplines in Hong Kong, found generally positive attitudes toward the use of generative AI in teaching and learning.

Although the literature indicates a growing body of research on AI in education, several significant gaps remain. First, most prior studies primarily focused on the technical effectiveness of AI in improving learning outcomes, yet paid limited attention to students' perspectives as the primary users, particularly within culturally specific contexts such as Indonesia. Second, research on cultural barriers in adopting AI as a learning companion remains scarce, despite the fact that cultural factors play a crucial role in shaping technology acceptance in developing countries.

Third, the long-term impact of AI adoption on students' academic autonomy has been insufficiently examined, especially in the context of mathematics learning, which requires logical reasoning and independent problem-solving skills. Fourth, much of the existing research has been conducted in developed countries with advanced technological infrastructures, raising concerns about the applicability of their findings to the Indonesian context, where challenges of accessibility and digital literacy are more pronounced. Fifth, studies that explicitly identify the drivers and barriers of AI adoption in learning remain limited, particularly those that take into account local cultural dimensions.

Based on the preceding discussion, this study aimed to analyze the perceived effectiveness of AI use on learning outcomes among students who actively utilize AI tools in their learning activities, examine the relationship between AI personalization and learning satisfaction, investigate the influence of perceived challenges and concerns on students' continued intention, and explore students' lived experiences and interpretations regarding the role of AI in supporting learning processes and academic interactions.

In this study, the key constructs are explicitly defined to avoid conceptual ambiguity. *AI effectiveness* refers to the extent to which students perceive AI tools support task completion, conceptual understanding, and learning efficiency. *AI personalization* is conceptualized as the perceived ability of AI systems to adapt feedback, explanations, and interaction patterns according to students' learning pace, preferences, and cognitive needs. *Concerns* represent students' perceived risks associated with AI use, including over-reliance, reduced independent thinking, data privacy issues, and ethical challenges related to academic integrity.

Finally, *satisfaction and continued intention* refer to students' affective evaluations of their AI-assisted learning experiences and their motivational willingness to continue using AI tools in future academic activities. These conceptual definitions guided the development of the research instruments, data collection procedures, and the interpretation of findings across both quantitative and qualitative phases of the study.

2. Methodology

This section presents a comprehensive overview of the research methodology employed to examine how Indonesian higher education students perceive and adopt AI as a learning companion, and how this adoption influences their academic autonomy. The methodology encompasses the research design, sampling strategies, data collection instruments and procedures, analytical techniques for both quantitative and qualitative data, and ethical protocols that ensured the integrity and rigor of this investigation.

2.1 Research Design

This study employed a sequential exploratory mixed-methods approach (Creswell & Creswell, 2018). This design was selected to obtain a comprehensive understanding of the relatively novel phenomenon of AI adoption as a learning companion in Indonesian higher education contexts. The approach integrated quantitative data from Likert-scale surveys to identify general patterns of AI perception and adoption, followed by qualitative data from in-depth interviews to explore underlying factors influencing adoption and its impact on students' academic autonomy. The justification for utilizing a sequential exploratory mixed-methods design rested on three primary considerations. First, the complexity of technology adoption phenomena necessitated an in-depth exploration from multiple perspectives. Second, there was a need to confirm and expand quantitative findings through qualitative perspectives that can provide a richer context and nuance. Third, the limited existing literature regarding Indonesian cultural contexts in AI adoption for learning required an exploratory approach to identify unique factors that may not be found in other cultural contexts.

2.2 Participants

The target population for this study consisted of all active students in the mathematics education program at Universitas Terbuka (UT) who had completed at least two semesters and had stable Internet access. The selection of this population was based on the characteristics of UT students, who are typically adult learners with strong independent learning experience, making them relevant for examining the impact of AI on academic autonomy. The sampling technique employed was purposive sampling with stratification based on several criteria. Stratification was conducted based on semester level, divided into early-stage (semesters 3–4), mid-stage (semesters 5–6), and advanced-stage (semesters 7–8).

While AI usage experience was operationalized as the duration since first use (>6 months, <6 months, and non-user), we recognized that temporal exposure does not necessarily reflect actual engagement. Therefore, AI usage intensity was measured separately through self-reported frequency of use (daily, several times per week, weekly, or rarely). This distinction enabled a clearer analytical separation between longitudinal exposure and behavioral engagement patterns. Demographic criteria were also considered by including students in the age range of 20 to 45 years and from various geographical backgrounds across Indonesia to ensure diverse cultural representativeness.

The quantitative survey collected data from 85 valid respondents among mathematics education students. This sample size justification was based on power analysis with a medium effect size (0.3), significance level $\alpha = 0.05$, and power = 0.80. For the qualitative interviews, the sample size was set at 20 participants based on the principle of theoretical saturation, with a distribution of 7 active AI users, 8 occasional users, and 5 non-users.

The participants in this study were undergraduate students with prior experience in using AI-based tools for academic purposes. To ensure the relevance and meaningfulness of their responses, only students who had used AI tools in their learning activities for at least three months were included in the main quantitative analysis. Participants were further categorized into active and occasional AI users based on the frequency and duration of their AI use. In addition, their level of AI literacy was measured using a self-report scale, so that the interpretation of questionnaire data could be grounded in their actual engagement with AI technologies.

2.3 Data Collection and Instrument

Data collection was conducted in two main phases over a 12-month timeline. The first phase consisted of a quantitative survey conducted over the first eight months. This began with instrument preparation and ethical clearance in months 1–2, followed by survey distribution in months 3–6, and concluded with follow-up and data cleaning in months 7–8. The survey instrument comprised a structured questionnaire with 33 items using a 5-point Likert scale, ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*). Constructs measured in the survey included perceived usefulness of AI, consisting of 8 items (Cronbach's alpha reliability of 0.89), ease of use with 7 items (α = 0.85), cultural and social factors with 9 items (α = 0.82), and impact on academic autonomy with 9 items (α = 0.87).

Instrument validation was conducted through content validity by three expert judges who were specialists in educational technology and educational psychology, as well as pilot testing with 30 respondents to ensure clarity and accuracy of the instrument. The survey collection procedure was conducted online using Google Forms distributed through Universitas Terbuka's learning management system. Reminders were sent to non-responders in the third and fifth weeks after initial distribution to increase the response rate. Each respondent who completed the survey received a "Thank you" confirmation and information about the next stage of the research.

The second phase consisted of qualitative interviews conducted during months 6−10. Although there was a partial overlap with the quantitative phase to support methodological triangulation, strict temporal and procedural boundaries were maintained to minimize data contamination. Survey data had been fully collected and locked before the interview phase began, and interview questions were designed not to influence participants' prior survey responses. The semi-structured interviews lasted 45 to 60 minutes and were conducted via Zoom with participants' informed consent for audio recording. The interview started with general questions about experiences with digital technology, followed by focused questions on AI use in learning, driving and inhibiting factors, shifts in learning patterns and academic autonomy, as well as cultural perspectives on AI. Each session was recorded through audio recordings and contemporaneous field notes.

2.4 Data Analysis Procedure

Quantitative data analysis began with descriptive analysis, exploring respondents' demographic characteristics through frequency distributions, percentages, and calculations of measures of central tendency and variability. Subsequently, assumption testing was conducted through normality, linearity, homoscedasticity, and multicollinearity tests, with variance inflation factor (VIF) criteria below 5. For inferential analysis, Pearson correlation tests were used to identify relationships among variables, and multiple linear regression with the ordinary least squares (OLS) method to predict the influence of various factors on students' academic autonomy.

In this study, qualitative analysis was conducted using a thematic analysis approach encompassing familiarization, initial coding, theme development, theme review, theme definition, and report production supported by representative participant quotes (Isnawan et al., 2024; Sridana et al., 2025; Sukarma et al., 2024). Analysis quality was maintained through inter-rater reliability (Cohen's kappa > 0.80), member-checking with key participants, and data triangulation with quantitative findings. Mixed-methods integration was realized through joint displays presenting quantitative and qualitative findings side by side, enabling the creation of meta-inferences that identify convergent and divergent findings and provide a more comprehensive understanding of the studied phenomenon.

2.5 Research Ethics

This research obtained ethical clearance from the Research Ethics Committee of Universitas Terbuka and complied with Indonesian Ministry of Research, Technology, and Higher Education Regulation No. 42 of 2017, with all ethical aspects designed to protect participants' rights, welfare, and scientific integrity. Informed consent was obtained through digital signatures for quantitative surveys and recorded verbal consent for qualitative interviews, accompanied by complete information sheets regarding objectives, procedures, risks, benefits, and participants' rights. Confidentiality and anonymity were strictly maintained through de-identification, anonymous data collection, encryption, password-protected files, and access being limited to the research team only.

The principle of voluntary participation was upheld with the right to withdraw at any time without consequences, without coercion or discrimination, and equal opportunities for all students meeting the inclusion criteria. Data will be stored for a maximum of five years post-publication, with secure deletion protocols and sharing only with explicit participant consent or for scientific verification with anonymized data. Cultural sensitivity was addressed through the use of local languages, scheduling that respected religious practices, and mitigation of power dynamics, while potential risks such as psychological discomfort, technology anxiety, and academic implications were minimized through briefings, technical support, and assurance of non-influence on participants' academic status.

3. Results and Findings

This study employed a mixed-methods approach to examine students' perceptions and experiences with AI in learning. A total of 85 mathematics education students from Universitas Terbuka participated in both a quantitative survey and qualitative open-ended questions, with 20 students participating in follow-up interviews. The findings are presented in two main sections: quantitative results analyzing relationships between key variables, and qualitative themes capturing students' lived experiences with AI as a learning companion.

3.1 Quantitative Findings

This study involved 85 mathematics education students from Universitas Terbuka who provided complete responses out of 100 distributed questionnaires (response rate 85%). Fifteen questionnaires were excluded from the analysis due to incomplete data. Respondents exhibited diverse characteristics in terms of age range (20–45 years), frequency of AI use (ranging from never to very frequently), and level of familiarity with AI technology (from not familiar to very familiar).

Descriptive statistics for the variables of AI effectiveness, AI personalization, concerns, and satisfaction with continued intention are presented in Table 1.

Table 1: Descriptive statistics of research variables

Variable	n	Mean	SD	Min	Max	Interpretation
AI effectiveness	85	3.714	0.509	2.43	5	High
AI personalization	85	3.757	0.562	2.50	5	High
Concerns	85	3.711	0.634	2.00	5	Moderate
Satisfaction and continued intention	85	3.533	0.637	1.33	5	High

The data in Table 1 demonstrate that the respondents rated AI effectiveness as high (M = 3.714, SD = 0.509), AI personalization as high (M = 3.757, SD = 0.562), and concerns as moderate (M = 3.711, SD = 0.634), while satisfaction and continued intention also tended to be rated as high (M = 3.533, SD = 0.637). The variability of responses, as reflected by the standard deviation values, was relatively consistent across the measured variables. Among them, the concerns variable exhibited the highest variability (SD = 0.634), indicating greater heterogeneity in respondents' levels of concern compared to their perceptions of AI effectiveness and personalization. Furthermore, the wide range between the minimum and maximum scores suggests substantial diversity in respondents' perceptions of AI use in learning, spanning from relatively negative to highly positive evaluations.

To address the first research question regarding how students' perceptions influence their satisfaction and continued intention to use AI, Pearson correlation analysis was employed. This analysis was selected to identify the presence of linear relationships between predictor variables and the criterion variable, as well as to determine the strength and direction of these relationships. Specifically, the correlation analysis examined three pairs of relationships: (1) AI effectiveness with satisfaction and continued intention, (2) AI personalization with satisfaction and continued intention, and (3) concerns with satisfaction and continued intention. Table 2 presents the complete results of the Pearson correlation analysis for these three relationships.

Table 2: Results of the Pearson correlation analysis

Relationship	r	t	df	R^2	Significance
AI effectiveness → Satisfaction and continued intention	0.512	5.426	83	26.2%	$p < 0.05$
AI personalization → Satisfaction and continued intention	0.556	6.097	83	30.9%	$p < 0.05$
Concerns → Satisfaction and continued intention	-0.043	-0.389	83	0.2%	$p > 0.05$

Note: r = Pearson correlation coefficient; t = t-statistic value; df = degrees of freedom; R^2 = coefficient of determination

The Pearson correlation analysis revealed a significant positive relationship between perceived AI effectiveness and respondents' satisfaction and continued intention ($r = 0.512$, $p < 0.05$), indicating a moderate association. The coefficient of determination ($r^2 = 0.262$) shows that perceived AI effectiveness explains 26.2% of the variance in respondents' satisfaction and continued intention. These findings indicate that higher perceived effectiveness of AI is associated with greater satisfaction and stronger intentions to continue using AI, without implying a causal relationship.

Second, AI personalization showed the strongest significant positive relationship with satisfaction and continued intention ($r = 0.556$, $t = 6.097$, $p < 0.05$) with a moderate correlation strength. AI personalization explained 30.9% of the variance in satisfaction and continued intention, which is higher than that for AI effectiveness. This finding indicates that the ability of AI to adapt content, delivery style, and learning pace to individual student needs plays a stronger role in influencing satisfaction and continued intention compared to general AI effectiveness.

Third, concerns about AI showed a very weak and non-significant negative relationship with satisfaction and continued intention ($r = -0.043$, $t = -0.389$, $p > 0.05$). This very small and non-significant correlation coefficient suggests that respondents' concerns regarding aspects such as dependency, plagiarism, or data privacy do not have a meaningful influence on their satisfaction and intention to continue using AI in learning. This finding differs from several previous studies that identified concerns as barriers to technology adoption, indicating that students in this study may have developed strategies to address these concerns.

The findings in Table 2 reveal that two of the three predictors (AI effectiveness and AI personalization) had significant positive correlations with satisfaction and continued intention, while concerns showed a non-significant correlation. Although these correlation results are informative, several important questions remain: When all three predictors are analyzed simultaneously, do all predictors remain significant? Which predictor provides the greatest contribution? What proportion of variance in satisfaction and continued intention can be explained by the overall model?

To answer these questions, multiple linear regression analysis was conducted using the ordinary least squares (OLS) method. Table 3 presents the complete results of the multiple regression analysis, including regression coefficients (unstandardized and standardized), significance tests for each predictor, model quality indicators (R^2, Adjusted R^2, F-statistic), and multicollinearity tests (VIF).

The multiple regression analysis (Table 4) yielded several important findings. The overall regression model was significant ($F(3, 81) = 13.199$, $p < 0.05$), indicating that the combination of AI effectiveness, AI personalization, and concerns together can predict students' satisfaction and continued intention. The model explained 32.8% of the variance in satisfaction and continued intention

(R^2 = 0.328), with an adjusted R^2 of 30.3%, suggesting that after adjusting for the number of predictors, the model maintained substantial predictive power.

Table 3: Results of multiple regression analysis: regression coefficients

Predictor	*B*	SE	*β*	*t*	VIF	Significance
Constant	0.963	0.566	-	1.700	-	$p > 0.05$
AI effectiveness	0.261	0.176	0.209	1.479	2.388	$p > 0.05$
AI personalization	0.450	0.159	0.397	2.825	2.384	$p < 0.05$*
Concerns	-0.024	0.092	-0.024	-0.262	1.003	$p > 0.05$

– *Model: Satisfaction and continued intention =* $\beta_0 + \beta_1$*(effectiveness) +* β_2*(personalization) +* β_3*(concerns)*
– **Significant at a = 0.05*
– *Note: B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; t = t-statistic value; VIF = variance inflation factor*

However, examination of the regression coefficients revealed interesting findings that differed from the previous correlation results. Of the three predictors, only AI personalization significantly predicted satisfaction and continued intention ($\beta = 0.450$, $t = 2.825$, $p < 0.05$). The standardized regression coefficient ($\beta = 0.397$) indicated that AI personalization had the strongest contribution in the model. Each one-unit increase in AI personalization increased satisfaction and continued intention by 0.450 units, holding other variables constant.

Table 4: Results of multiple regression analysis: model summary

Statistic	Value	Interpretation
R	0.573	Multiple correlation
R^2	0.328	Model explains 32.8% of variance
Adjusted R^2	0.303	Adjusted for number of predictors
Standard error	0.535	Average prediction error
$F(3, 81)$	13.199	Overall model significance
Significance	$p < 0.05$	Model is significant

A surprising finding was that AI effectiveness did not significantly predict satisfaction and continued intention ($\beta = 0.261$, $t = 1.479$, $p > 0.05$), despite showing a significant positive correlation in the bivariate analysis. This phenomenon suggests a suppression effect or mediation, where the influence of AI effectiveness on satisfaction and continued intention may operate through AI personalization. In other words, when AI personalization is included in the model, the unique contribution of AI effectiveness becomes non-significant because most of its variance is already explained by personalization.

Concerns also did not significantly predict satisfaction and continued intention ($\beta = -0.024$, $t = -0.262$, $p > 0.05$), consistent with the previous correlation results. The very small negative regression coefficient indicates that concerns have no meaningful influence in the model, either bivariate or multivariate. The multicollinearity test revealed no issues in the model, with all VIF values < 5 (effectiveness = 2.388; personalization = 2.384; concerns = 1.003). These low VIF values indicate no high correlations among predictors that could affect the stability of regression coefficient estimates. Therefore, the analysis results are reliable and not influenced by multicollinearity problems.

3.2 Qualitative Findings

To explore students' lived experiences with AI as a learning companion and to triangulate and enrich the quantitative findings, thematic analysis was conducted on responses from 85 participants to open-ended questions. Following Braun and Clarke's (2006) six-phase framework, the analysis progressed iteratively through familiarization, initial coding, theme development, theme review, theme definition, and report production. This process resulted in three superordinate themes with several sub-themes, which were used to explain, contextualize, and validate patterns observed in the survey results, particularly regarding students' engagement, perceived usefulness, and dependency on AI as an academic partner.

3.2.1 Theme 1: The ambivalent experience of AI use

The first superordinate theme captures the fundamentally dualistic nature of participants' experiences with AI as a learning companion. Participants simultaneously embraced the affordances of AI while grappling with its limitations, ultimately developing sophisticated adaptive strategies to navigate the tension between benefits and risks.

Table 5 presents a comprehensive overview of participants' experiences with AI, categorized into three overarching dimensions: positive experiences, negative experiences, and adaptive strategies. This tripartite organization highlights the inherently ambivalent nature of student-AI interactions—participants simultaneously embraced the advantages of AI while contending with its limitations, ultimately developing nuanced strategies to manage this tension. The dominant positive theme was operational efficiency (52.9%, n = 45), where participants emphasized the ability of AI to expedite task completion and reduce cognitive workload.

Many described AI as a tool that "*facilitates assignment work with efficiency*" and "*helps complete tasks faster*", underscoring its role in supporting distance learners juggling multiple responsibilities. Knowledge accessibility (44.7%, n = 38) emerged as another major benefit, as participants appreciated the capacity of AI to provide "*detailed and easy-to-understand explanations*" and to offer relevant journal references, signifying its role as both a learning enhancer and an academic resource. A smaller subset (14.1%, n = 12) mentioned creative ideation, viewing AI as a "*thinking partner*" that stimulated original insights rather than merely retrieving existing information.

Table 5: Participants' experiences with AI: positive, negative, and adaptive dimensions

Dimension	Sub-theme	n	%	Representative quote
Positive experiences	Operational efficiency	45	52.9	*"Positively facilitates assignment work with efficiency... helps complete tasks faster"* (P1)
	Knowledge accessibility	38	44.7	*"Discussion is quite detailed and easy to understand... can help provide several journal references"* (P3)
	Creative ideation	12	14.1	*"Very helpful because it can help increase creativity"* (P3)
Negative experiences	Informational inaccuracy	32	37.6	*"Answers are often erroneous, especially in calculations... many errors with mathematical symbols"* (P1)
	Cognitive atrophy	28	32.9	*"Students no longer want to think because of using AI... too dependent"* (P2, P6)
	Linguistic complexity	15	17.6	*"Sometimes the language used is too heavy... difficult to create appropriate prompts"* (P4, P5)
Adaptive strategies	Active verification	25	29.4	*"Cross-check from various Internet pages... think more diligently before accepting answers"* (P1)
	Creative paraphrasing	20	23.5	*"Paraphrase every sentence searched from AI... must be understood and edited first"* (P3, P9)
	Usage limitation	18	21.2	*"As much as possible, do the assignment first, but if it's too difficult, then use AI"* (P5)

Conversely, participants also articulated notable negative experiences, particularly concerning informational inaccuracy (37.6%, n = 32), where AI-generated responses were often "*erroneous, especially in calculations*" or contained "*many errors with mathematical symbols*". This was a critical issue among mathematics education students who required computational precision. Cognitive atrophy (32.9%, n = 28) represented another key concern, with participants fearing that over-reliance on AI might diminish their willingness to think independently. Additionally, linguistic complexity (17.6%, n = 15) surfaced as a barrier, as some participants found the language of AI "*too heavy*" and struggled to "*create appropriate prompts*", indicating varying levels of digital literacy.

In response to these challenges, participants developed adaptive strategies such as active verification (29.4%, n = 25) by cross-checking AI outputs with authoritative sources, creative paraphrasing (23.5%, n = 20) to maintain originality and understanding, and usage limitation (21.2%, n = 18) to preserve critical engagement by attempting tasks before consulting AI. Collectively, these findings demonstrate that students are not passive consumers of technology but active, reflective agents capable of responsible and adaptive engagement with AI-enhanced learning environments, evidenced by the fact that 73.5% of participants reported employing at least one adaptive strategy.

Figure 1 illustrates the relative prevalence of each thematic category, allowing immediate comparison across experience dimensions.

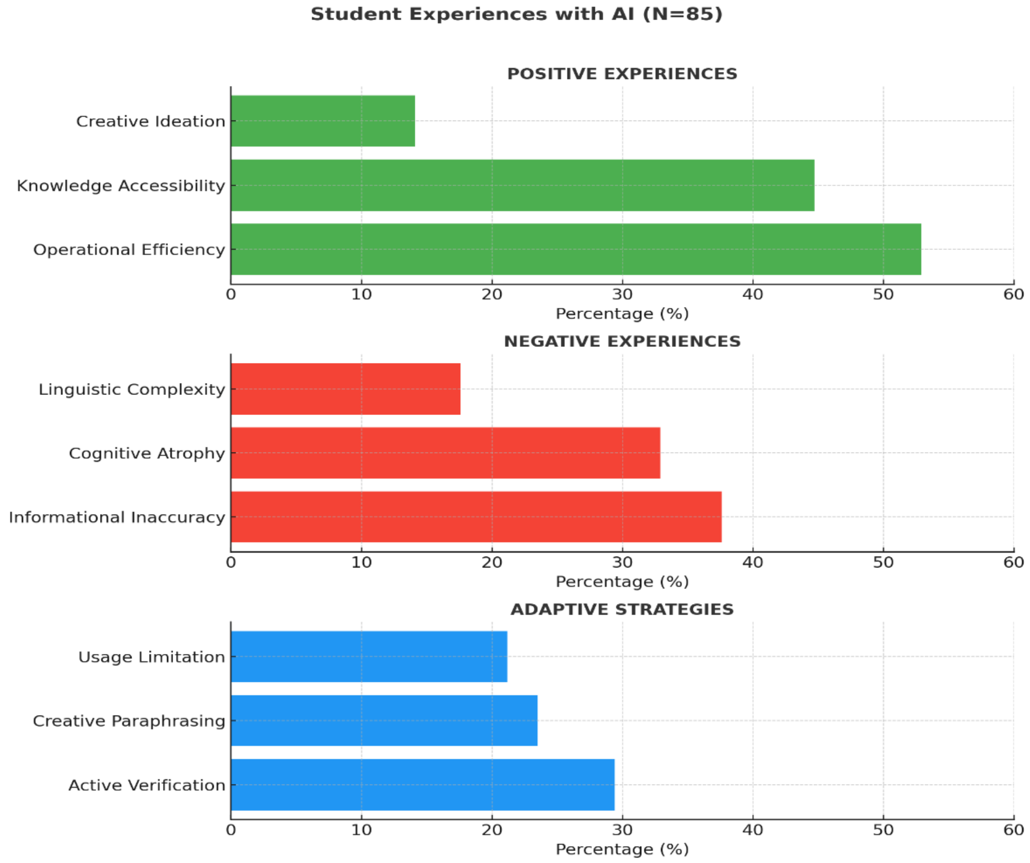

Figure 1: Descriptive representation of thematic experience dimensions related to AI use

Overall, positive experiences outweighed negative ones in absolute frequency. Operational efficiency (52.9%) and knowledge accessibility (44.7%) emerged as the most common benefits, surpassing the most frequent negative experience, informational inaccuracy (37.6%). This pattern indicates a generally positive perception of AI among students. However, the substantial presence of negative themes underscores that the benefits of AI coexist with legitimate concerns rather than overshadowing them entirely. Positive and negative experiences appear to interact in a nuanced balance, reflecting the coexistence of opportunity and risk in students' engagement with AI technologies.

The discrepancy between positive experience frequencies and adaptive strategies reveals an important behavioral dynamic. While 52.9% of participants reported enhanced operational efficiency, only 29.4% indicated engaging in active verification practices. This 23.5-percentage-point gap suggests that not all students who benefit from AI simultaneously adopt critical evaluation habits, leaving some potentially vulnerable to the pitfalls of uncritical reliance. Moreover, the relatively low frequency of creative ideation (14.1%) points to underutilized potential, possibly due to limited competencies or academic task structures that do not yet encourage creative AI use. Encouragingly, approximately three-quarters of participants reported employing at least one adaptive strategy, signaling considerable agency and resourcefulness. This finding challenges deficit narratives that portray students as passive recipients of technology, highlighting instead their capacity to self-regulate and engage responsibly with AI.

3.2.2 Theme 2: The dual influence of AI on collaborative learning
The second superordinate theme reveals a complex, seemingly contradictory pattern regarding the role of AI in academic interactions and collaborative processes. Participants' perspectives diverged significantly, with some viewing AI as a collaborative facilitator, others as an inhibitor, and many recognizing that its impact depends fundamentally on context and implementation. This complexity therefore necessitates a deeper analysis of how AI-supported idea formulation is situated within collaborative learning practices and how it influences the quality of peer interaction. AI supports idea formulation by helping students generate, structure, and expand their initial thoughts before collaborative activities. This can enrich collaborative learning by improving the readiness and quality of student contributions. However, without proper guidance, AI may also weaken direct peer interaction by replacing rather than supporting collaborative cognitive efforts.

Table 6 summarizes the findings concerning the influence of AI on academic interactions and collaborative learning. The data reveal a nuanced pattern that resists simple categorization of AI as either a collaborative facilitator or inhibitor. Three major perspectives emerged. First, many participants perceived AI as a facilitation tool, with 25.9% describing it as a communication mediator that helped articulate ideas and clarify exchanges with peers or instructors. Another 21.2% viewed AI as a discussion catalyst, using it to generate perspectives that enriched group dialogue, while 17.6% identified it as a knowledge equalizer, noting that AI provided accessible information that reduced disparities among group members. Collectively, these accounts position AI as a supportive agent that enhances interaction quality, idea generation, and knowledge parity in collaborative settings.

At the same time, a substantial proportion of participants (35.3%) identified AI as an inhibitor of collaboration, noting that reliance on AI often reduced direct peer engagement, as individual consultation with AI was faster than group coordination. Another 14.1% reported challenges in attributing authorship and distinguishing human from AI contributions, which blurred accountability in groupwork. Interestingly, nearly one-quarter of participants (24.7%) adopted a context-dependent view, asserting that AI could either facilitate or hinder collaboration depending on how it was used. This recognition underscores that the effects of AI arise not inherently from the technology but from its pedagogical integration and social context. Overall, the distribution of responses highlights both the risks of unstructured AI use and the potential for thoughtful instructional design to transform AI from a source of isolation into a catalyst for meaningful collaboration.

Table 6: The role of AI in academic interactions and collaboration

Impact type	Sub-theme	n	%	Representative quote
Facilitation	Communication mediator	22	25.9	*"AI has a positive impact on student and lecturer interactions... helps with idea formulation"* (P1)
	Discussion catalyst	18	21.2	*"Several views that can support opinions in group discussions... provides ideas for discussion"* (P3)
	Knowledge equalizer	15	17.6	*"There is quite efficient knowledge... helps learning become easier"* (P3)
Inhibition	Reduced peer interaction	30	35.3	*"Inhibits because assignments are done entirely through AI... no interaction because dependent"* (P2, P5)
	Ambiguous attribution	12	14.1	*"Difficult to distinguish between one's own work results and AI's"* (P8)
Contextuality	Context-dependent effects	21	24.7	*"Could inhibit, could encourage, depending on its use... depends how we use it"* (P5)

Figure 2 illustrates the trichotomy of participant perspectives on the collaborative impact of AI, revealing that no single viewpoint predominated.

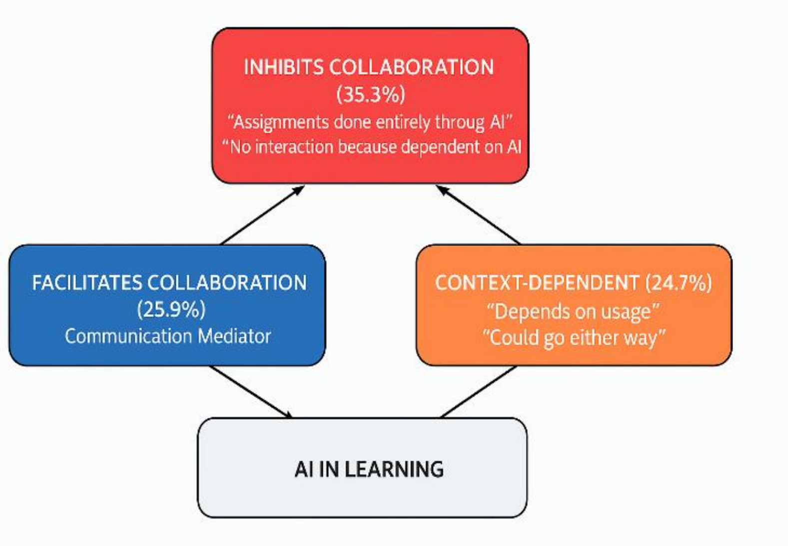

Figure 2: Trichotomy of perspectives on the collaborative impact of AI

While the largest share of participants (35.3%) perceived AI as inhibiting collaboration, this represents only about one-third of the sample, far from a consensus. A considerable proportion viewed AI as facilitative (25.9% explicitly, with additional sub-themes such as catalyst and equalizer roles), and nearly one-quarter (24.7%) adopted a context-dependent stance, recognizing that the influence of AI varies with its application. This distribution challenges deterministic narratives on both ends of the spectrum, disputing assumptions that AI either inherently promotes or inevitably hinders collaboration. Instead, the findings highlight that students' experiences with AI emerge from the interplay among technology, pedagogy, and social context rather than from the technology itself.

The prevalence of context-dependent views (24.7%) demonstrates participants' growing metacognitive awareness that the collaborative effects of AI hinge on implementation choices. These participants recognized that AI can either facilitate or inhibit group learning depending on how it is integrated into instructional design, indicating potential as peer mentors in promoting strategic, reflective use. Conversely, the fact that inhibition remains the single most common perception underscores limitations in current, unguided AI use: when students employ AI individually without structured pedagogical direction, solitary rather than collective engagement tends to dominate.

Meanwhile, the facilitative cluster, comprising communication mediation, discussion catalysis, and knowledge equalization, suggests multiple pathways for enhancing collaboration, though these benefits appear contingent on specific learning conditions. Understanding what differentiates facilitative from inhibitive experiences could inform future interventions designed to cultivate more collaborative, purposeful engagement with AI.

3.2.3 *Theme 3: Systemic challenges of AI integration*

The third superordinate theme addresses institutional and systemic challenges that AI integration poses for higher education, extending beyond individual user experiences to structural implications. These challenges emerged across three interconnected dimensions, epistemological, pedagogical, and social, each requiring coordinated institutional responses rather than individual adaptation alone.

Table 7 highlights that AI integration introduces systemic challenges in higher education that extend beyond individual usage to institutional and epistemic dimensions. Nearly one-third of participants (32.9%) identified epistemological difficulties in verifying the accuracy and credibility of AI-generated information. Many reported that AI responses often contain factual or contextual errors, particularly in quantitative subjects, and those outputs may seem convincing yet lack reliability.

This situation creates a validation crisis in which traditional cues for assessing credibility, such as authorship, credentials, or source transparency, no longer apply. The challenge intensifies when AI fabricates realistic but non-existent citations, undermining the integrity of scholarly communication. These findings underscore the urgent need for institutions to develop structured instruction in evidence evaluation and verification practices, as relying on students to acquire such skills independently is no longer sufficient in an AI-mediated learning environment.

Table 7: Institutional and systemic challenges posed by AI

Challenge type	Description	n	%	Representative quote	Implications
Epistemological	Difficulty validating AI-generated information; uncertainty about accuracy; fabricated citations	28	32.9	*"Many calculations contain errors... answers from AI not always relevant"* (P1, P7)	Need for verification literacy; crisis of epistemic authority
Pedagogical	Difficulty distinguishing authentic student work from AI-generated submissions; assessment validity concerns	25	29.4	*"Difficult to distinguish between one's own work results and AI's"* (P8)	Need for process-based assessment; authentic task design
Social	Differential access to and proficiency with AI tools; digital divide; skills disparities	18	21.2	*"Difficult to create prompts that match material... sometimes language too heavy"* (P5, P4)	Need for explicit AI literacy instruction; equity concerns

Pedagogical issues also emerged prominently, with 29.4% of participants acknowledging the difficulty educators face in distinguishing authentic student work from AI-generated content. This authenticity dilemma destabilizes the foundation of traditional assessment, as the capacity to verify whether submissions truly reflect student learning becomes uncertain. When essays, reports, and problem sets can be completed by AI tools, grading systems risk losing their function as indicators of genuine competence.

Consequently, institutions must re-envision assessment design, shifting from evaluating static products toward assessing dynamic processes of knowledge construction. This pedagogical transformation calls for substantial capacity-building among instructors and restructured institutional policies that promote transparency, formative assessment, and the cultivation of higher-order cognitive skills rather than mere task completion.

The social dimension, reported by 21.2% of participants, centers on inequities in AI access and proficiency. Participants described difficulties in crafting effective prompts and interpreting AI outputs that often use overly complex language, signaling unequal digital literacy levels. These disparities—spanning infrastructure access, skills competence, and strategic understanding—risk deepening academic inequality. Students adept at navigating AI gain disproportionate advantages, while those lacking access or proficiency are left behind. If unaddressed, AI risks becoming a mechanism of exclusion rather than empowerment. Therefore, institutions must pursue comprehensive responses, ensuring equitable technological access, integrating AI literacy into curricula, and designing inclusive assessment frameworks. Collectively, these epistemological, pedagogical, and social challenges reveal that AI integration represents not a mere technological shift but a systemic transformation demanding coordinated institutional adaptation across all dimensions of academic practice.

Figure 3 illustrates the interrelated nature of systemic challenges and their institutional implications, emphasizing that these three categories of challenges cannot be addressed in isolation but require a coordinated and comprehensive institutional response.

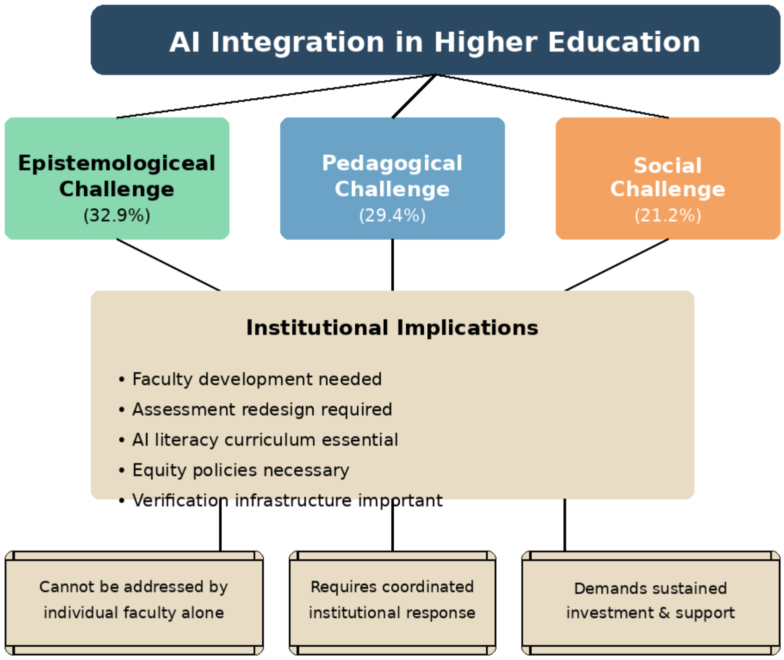

Figure 3: Interconnected systemic challenges

The figure positions AI integration as a catalyst for three simultaneous and interconnected challenges, epistemological, pedagogical, and social, each possessing distinct characteristics yet sharing overlapping implications. The epistemological challenge (32.9%) reflects a crisis of knowledge validation: determining what constitutes truth when AI can confidently present false or misleading information. This issue permeates all academic disciplines but manifests differently across fields, ranging from computational errors in mathematics to fabricated citations in the humanities to plausible yet inaccurate explanations in the sciences.

Addressing this challenge necessitates cultivating verification literacy as a core educational objective, integrated across curricula as an epistemic practice rather than a standalone technical skill. The pedagogical challenge (29.4%) focuses on maintaining assessment authenticity in an era where AI can complete conventional assignments. It compels educators to rethink the very purpose of assessment: while traditional tests of knowledge recall or routine application loses validity in the AI context, assessments emphasizing synthesis, contextual reasoning, and metacognitive reflection remain resilient, and may even benefit from AI-assisted learning. This challenge thus serves as a driver for pedagogical transformation, though it requires significant instructor training and institutional support.

The social challenge (21.2%) centers on ensuring that AI integration does not exacerbate educational inequities. This issue intersects with both epistemological and pedagogical dimensions, as students who lack verification skills or AI literacy face compounded disadvantages in learning outcomes. True equity extends beyond technological access; it encompasses equitable access to the knowledge, training, and critical thinking skills necessary for effective AI use, a distinction often neglected in technology equity initiatives. The lower section of Figure 3 underscores that these intertwined challenges surpass the capacity of individual educators to solve through classroom-level innovation alone.

Comprehensive institutional strategies are essential, including faculty development programs to enhance AI literacy, curricular revisions to embed verification and ethical reasoning skills, equitable infrastructure investments, and robust policy frameworks guiding responsible AI adoption. The figure concludes by emphasizing that sustainable and effective responses "demand sustained investment and support", recognizing AI integration as an enduring institutional transformation akin to past revolutions in educational technology, such as the adoption of personal computers or the Internet—but potentially more profound given the unique ability of AI to perform cognitive, rather than merely computational, work.

4. Discussion

Before discussing the main findings, it is important to clarify the composition of respondents in terms of their AI usage experience. Respondents were categorized as active users, occasional users, and non-users, reflecting varying levels of AI literacy and familiarity. Throughout the analysis, particular attention was paid to differentiating perspectives according to these groups. For instance, richer and more detailed responses generally originated from active users with longer and more frequent engagement with AI tools, while occasional and non-users tended to provide more tentative or general perceptions. This stratification ensures that interpretations of attitudes and reported experiences are grounded in the respondents' actual exposure to and maturity with AI technology, addressing potential concerns about the plausibility of certain responses.

This study examined the complex relationships between AI effectiveness, AI personalization, concerns, and students' satisfaction with continued intention to use AI in higher education, while also exploring the lived experiences and systemic implications of AI integration. The findings reveal several important patterns that both align with and challenge existing literature, offering new theoretical insights into student-AI relationships in educational contexts.

4.1 The Personalization Imperative: A Critical Success Factor

One of the most striking findings from the quantitative analysis is that AI personalization emerged as the sole significant predictor of satisfaction and continued intention ($\beta = 0.450$, $p < 0.05$), explaining 32.8% of the variance in the regression model. This finding strongly aligns with recent research emphasizing the critical role of personalization in educational technology adoption. Almusfar (2024) and Noviyanti et al. (2025) demonstrated that personalized e-learning experiences significantly enhance student satisfaction and engagement, while Ansari and Qamari (2025) found that intelligent systems providing tailored educational content substantially improve learning outcomes. The primacy of personalization over general effectiveness in this study extends these findings by demonstrating that adaptation to individual needs represents not merely an enhancement but the fundamental driver of sustained AI adoption.

This result can be theoretically situated within self-determination theory (SDT), which posits that technologies supporting autonomy, competence, and relatedness enhance intrinsic motivation and sustained engagement (Ryan & Deci, 2020; Noviyanti, 2019). Personalized AI systems that adapt to individual cognitive levels, learning styles, and contextual needs may satisfy these psychological needs more effectively than generically effective but impersonal systems. When AI demonstrates understanding of a student's unique situation through tailored responses, it signals recognition of the learner as an individual rather than a generic user, thereby fostering a sense of competence and autonomy that drives continued engagement.

The qualitative findings complement this quantitative result by revealing what personalization means from students' perspectives. Students explicitly valued the capacity of AI to provide "*detailed and easy to understand*" explanations adapted to their comprehension levels, while simultaneously expressing frustration when AI outputs felt generic or required extensive prompt engineering to achieve relevance. This expectation gap, between desired and experienced personalization, explains why high mean ratings of personalization (M = 3.757) coexist with its critical importance as a predictor. Students recognize the value of personalization but perceive current implementations as falling short of their expectations, suggesting substantial room for improvement in adaptive algorithm development.

4.2 The Effectiveness Paradox: Indirect Pathways to Adoption

The apparent contradiction between correlation and regression results for AI effectiveness presents a theoretically intriguing pattern. While effectiveness showed a significant positive correlation with satisfaction and continued intention ($r = 0.512$, $p < 0.05$), it became non-significant in the multivariate model ($\beta = 0.261$, $p > 0.05$). This suppression effect suggests that effectiveness operates through personalization rather than directly influencing behavioral intentions, a finding that challenges traditional technology acceptance model (TAM) assumptions about the direct impact of perceived usefulness on intention.

This pattern diverges from conventional TAM research (Al-Daihani, 2016; Bravo et al., 2025), which typically positions perceived usefulness as a direct predictor of behavioral intention. However, our findings align more closely with extended TAM models that incorporate mediating variables, such as perceived usefulness and personalization, as shown in previous studies on educational AI adoption. While prior research tends to assume that AI effectiveness directly influences students' intention to use (e.g., through perceived ease and usefulness), our results reveal a more nuanced process. Specifically, we identified an effectiveness paradox, where the general capabilities of AI do not automatically translate into sustained adoption unless they are transformed through personalization into situated usefulness.

This finding contrasts with traditional TAM-based approaches that emphasize linear relationships between effectiveness and usage intention, suggesting instead that in educational contexts, where learning needs and cognitive profiles are highly individualized, effectiveness must first be contextualized and internalized by learners. Thus, our study extends existing TAM research by highlighting personalization as a critical intervention point rather than a secondary moderator.

The qualitative data illuminate the mechanism underlying this statistical pattern. Participants consistently described AI as "*efficient*" and "*fast*" (52.9% mentioning operational efficiency) but simultaneously noted that outputs required verification, editing, and adaptation to their specific needs. As Participant 1 articulated, AI "*positively facilitates assignment work with efficiency*", yet "*answers are often erroneous, especially in calculations*". This juxtaposition reveals that students value the speed of AI but recognize that velocity alone does not ensure satisfaction; the outputs must also fit their particular cognitive and contextual requirements. Personalization serves as the critical link converting abstract effectiveness into concrete value for individual learners.

This finding carries important implications for cognitive load theory (Sweller et al., 2019). Effective but impersonal AI may actually increase extraneous cognitive load by requiring students to invest substantial mental effort translating generic outputs into personally meaningful content, verifying accuracy, and adapting language to their comprehension level. Personalized AI reduces this translation burden by generating outputs that better match users' needs from the outset, thereby freeing cognitive resources for germane processing, the effortful learning that builds schemas and expertise. The effectiveness paradox thus reflects a deeper truth: tools that appear efficient at the surface level may impose hidden cognitive costs that personalization helps mitigate.

4.3 Concerns as Non-Barriers: Generational Shift in Technology Relationships

The finding that concerns showed no significant relationship with satisfaction or continued intention (r = -0.043, p > 0.05) challenges decades of technology adoption research emphasizing barriers and resistance. Traditional models treat perceived risks as negative predictors of adoption, yet our data reveal a more complex reality, particularly for digitally native populations. This pattern contrasts with earlier educational technology research but aligns with emerging studies on Generation Z's pragmatic technology attitudes (Seemiller & Grace, 2016).

The qualitative findings provide crucial insight into this counterintuitive pattern. Despite 32.9% of participants expressing concerns about cognitive atrophy and 37.6% noting informational inaccuracy, a remarkable 73.5% reported employing adaptive strategies – active verification (29.4%), creative paraphrasing (23.5%), or usage limitation (21.2%) – to manage these risks. This pattern suggests that concerns do not inhibit usage but rather shape how usage occurs, transforming anxiety into productive critical engagement. As Participant 1 exemplified, students "*cross-check from various Internet pages*" and "*think more diligently before accepting answers*", converting skepticism into verification practices.

This adaptive response can be understood through the lens of resilience theory, which emphasizes individuals' capacity to develop coping mechanisms when confronting stressors (Masten, 2014). The digital natives in our sample appeared to treat AI concerns as manageable challenges requiring strategic responses rather than insurmountable obstacles demanding avoidance. This resilience likely stems from lifelong exposure to algorithmic systems, recommendation engines, autocorrect, and search algorithms that have taught this generation to maintain healthy skepticism while leveraging the benefits of technology. They have developed what might be termed *critical AI literacy*: the capacity to use AI strategically while maintaining epistemic authority over its outputs.

However, this interpretation requires qualification. The non-influence of concerns may reflect not universal adaptation but rather selection bias; students who could not manage concerns may have ceased AI usage and thus did not appear in our convenience sample of current users. Longitudinal research tracking students from initial AI exposure through sustained usage would clarify whether adaptive strategies develop universally or whether some students abandon AI due to unmanageable concerns. Additionally, the specific concerns measured in our study (dependency, accuracy, privacy) may not capture the full spectrum of anxieties students experience, particularly regarding ethical implications or employment displacement that might influence attitudes differently.

4.4 Collaborative Ambivalence: Context Trumps Technology

The qualitative findings on the collaborative impact of AI reveal profound ambivalence, with substantial proportions of participants viewing AI as facilitating (25.9%), inhibiting (35.3%), or having context-dependent effects (24.7%) on collaboration. This trichotomy challenges deterministic narratives while providing a nuanced understanding of when and how AI supports or undermines collaborative learning. The finding that inhibition represents the single largest perspective (though not a majority) suggests that default, unstructured AI usage patterns lean toward individualization rather than collectivization of learning, a concerning pattern given the well-established benefits of collaborative learning for deep understanding (Johnson & Johnson, 2009).

This ambivalence aligns with recent research by Alyoussef et al. (2025) and Kang et al. (2025), who found that the collaborative effects of AI depend critically on pedagogical design and implementation context. Our data extend these findings by identifying specific mechanisms through which AI facilitates collaboration: serving as a communication mediator that helps articulate ideas (25.9%), functioning as a discussion catalyst providing diverse perspectives (21.2%), and acting as a knowledge equalizer reducing preparation disparities (17.6%). Conversely, AI inhibits collaboration by making individual consultation faster than group coordination (35.3%) and complicating work attribution (14.1%).

The substantial context-dependent perspective (24.7%) represents sophisticated metacognitive awareness that technology effects emerge from human-technology interaction rather than inhering in the technology itself. These participants recognized that the same AI tool can facilitate or inhibit collaboration depending on task structure, group norms, and usage patterns. This understanding aligns with sociocultural perspectives on technology (Wertsch, 1991), which emphasize that the effects of tools depend on how they mediate social practices rather than on their inherent properties. A calculator facilitates mathematical collaboration when students use it to explore "what if" scenarios together, but inhibits collaboration when each student independently computes answers.

From a communities of practice perspective (Lave & Wenger, 1991), the collaborative impact of AI depends on whether it is positioned as a tool for collective knowledge construction or individual knowledge acquisition. When groups use AI to generate initial ideas that members then critique, elaborate, and synthesize, AI enhances the community's epistemic resources. However, when individuals use AI to complete their portions of groupwork independently, it fragments the collective learning process, transforming collaboration into mere task division. Educators must therefore design collaborative tasks that position AI as a thinking partner for groups rather than a substitute for human interaction—requiring explicit instruction in collaborative AI usage patterns.

4.5 Systemic Challenges: Beyond Individual Adaptation

The emergence of three systemic challenges – epistemological (32.9%), pedagogical (29.4%), and social (21.2%) – reveals that AI integration poses institutional-level disruptions exceeding individual adaptation capacity. These findings resonate with recent scholarship on the transformative impact of AI on higher education (Arriazu, 2025; Martínez et al., 2025) while providing an empirical grounding for theoretical discussions of the epistemic implications of AI.

The epistemological challenge reflects what Popkov and Barrett (2024) termed a "*validation crisis*": when AI confidently presents misinformation, traditional credibility heuristics fail. The students in our study noted that AI outputs "*are often erroneous, especially in calculations*", yet appear authoritative, creating what Jain et al. (2025) described as an "*illusion of knowledge*", false confidence in understanding based on AI-generated but unverified information. This challenge is particularly acute given the documented tendency of AI toward hallucination and citation fabrication (Aiumtrakul et al., 2023), which undermines the foundational assumption of scholarly discourse that references point to retrievable sources.

From an epistemological standpoint, this validation crisis challenges the traditional *correspondence theory of truth*, which holds that knowledge claims correspond to objective reality (Lynch, 2001). When AI can generate plausible-seeming but false claims, determining correspondence becomes problematic without extensive verification, a burden for which many students lack the skills to undertake. Educational institutions must therefore shift from assuming that students possess verification skills to explicitly teaching what might be termed *AI-era epistemic practices*: understanding the limitations of AI, recognizing hallucination patterns, triangulating information across sources, and maintaining appropriate epistemic humility about AI-derived knowledge.

The pedagogical challenge, namely, difficulty distinguishing authentic student work from AI-generated content, threatens assessment validity, as confirmed by Poell et al. (2025) and Reihanian et al. (2025). Our findings suggest that this is not merely a detection problem but a fundamental questioning of what should be assessed. If AI can complete traditional assignments, those assignments may be testing compliance rather than competence. This challenge catalyzes potentially productive pedagogical transformation, shifting from knowledge demonstration to knowledge construction, from product to process, from isolated to contextualized performance. However, this transformation requires substantial instructor capacity-building that many institutions have yet to provide systematically.

The social challenge, differential AI access and proficiency creating new inequalities, intersects with long-standing concerns about digital divides (Martínez et al., 2025). Our data reveal that this divide operates at multiple levels: infrastructure access (devices, Internet, premium subscriptions), skills competence (prompt engineering, output evaluation), and strategic knowledge (knowing when and how to use AI productively). Students lacking any of these dimensions face compounded disadvantages. As Participant 5 noted, it is "*difficult to create prompts that match material*", indicating that AI proficiency represents a prerequisite for academic success that not all students possess equally. This pattern threatens to transform AI from a democratizing force into a mechanism reinforcing existing inequalities, particularly if institutions fail to provide explicit AI literacy instruction and equitable access.

5. Limitations and Future Directions

Several limitations warrant acknowledgment. The cross-sectional design precludes causal inference, though the mixed-methods approach provides stronger warrants for interpreting relationships than quantitative analysis alone would permit. The convenience sample from a single institution may limit generalizability, particularly given Universitas Terbuka's distinctive population of adult distance learners. The measurement of "satisfaction and continued intention" as a single construct may lack sensitivity to distinguish affective satisfaction from behavioral intentions. Additionally, self-reported data may over-represent socially desirable behaviors (verification, critical usage) while under-representing potentially problematic ones (uncritical copying).

Future research should employ longitudinal designs tracking how student-AI relationships evolve as both AI capabilities advance and usage patterns stabilize. Experimental studies manipulating personalization features could test causal claims about the critical role of personalization. Comparative research across institutions, disciplines, and cultural contexts would illuminate boundary conditions for observed patterns. Most critically, research should investigate the 67.2% unexplained variance, testing expanded models that incorporate digital literacy, metacognitive awareness, task-technology fit, and social influence as additional predictors of AI adoption and satisfaction.

6. Conclusion

This study addressed how AI is meaningfully adopted in higher education and demonstrated that existing technology acceptance frameworks require theoretical refinement when applied to educational AI contexts. Rather than operating through a direct effectiveness-to-adoption pathway, our findings suggest that sustained AI engagement depends on how technological effectiveness is pedagogically translated into personalized and contextually relevant learning support. This conceptual shift reframes personalization from a supplementary feature into a central mechanism that shapes students' long-term relationship with AI.

Beyond individual attitudes, the study highlights the emergence of a new form of critical AI literacy, where students negotiate risks and benefits through strategic and reflective use, rather than passive acceptance or rejection. These insights underscore that AI integration in higher education cannot be approached as mere technological enhancement but as a systemic transformation involving epistemological, pedagogical, and institutional dimensions. Accordingly, future AI implementation should move toward adaptive, context-sensitive design and be accompanied by institutional policies that strengthen verification literacy, protect academic integrity, and promote equitable access. This will ensure that AI becomes a responsible partner in knowledge construction rather than a shortcut for cognitive outsourcing.

7. Conflict of Interest

The authors declare no conflicts of interest. The research funding from Universitas Terbuka did not influence the study design, data collection, analysis, interpretation, or publication decisions. All authors confirm the absence of competing interests.

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9. Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that ChatGPT was used solely for language editing, including improving clarity and grammatical accuracy. It did not contribute to the research content, analysis, or interpretation. All scientific content remains the sole responsibility of the authors.

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