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University students' attitudes towards AI-enabled learning enjoyment: Evidence from the Philippines

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Abstract:

As artificial intelligence (AI) tools increasingly shape higher education, understanding their impact on students' motivation and learning experiences is essential. This study investigated university students' attitudes towards AI and its role in enhancing learning enjoyment. A total of 220 university students from Regions XI and XII in the Philippines participated in the study during the second quarter of 2025, using an instrument based on the Technology Acceptance Model (TAM) and Self-determination Theory (SDT). Data were analysed using descriptive statistics and factor analysis. The measurement model showed satisfactory reliability (Cronbach's alpha=0.759 to 0.914). Using Principal Axis Factoring with Promax rotation, strong factor loadings (λ=0.414 to 0.946) emerged, along with acceptable model fit indices (CFI=0.916, TLI=0.901, RMSEA=0.0873, SRMR=0.086). While students generally reported positive experiences with AI tools, concerns regarding creativity loss, over-reliance, and occasional confusion were also noted. These findings suggest that AI integration should balance technical benefits with pedagogical considerations to support both academic performance and student well-being. Limitations include the cross-sectional design and focus on university-level participants, suggesting the need for longitudinal and multi-context studies.

Keywords: **AI in education, educational technology, intrinsic motivation, learning engagement, student perceptions.**

Classification numbers: **1.3, 3.4**

1. Introduction

The integration of AI into educational settings has become a major area of inquiry, as digital technologies increasingly shape higher education worldwide [1]. As AI continues to advance, its capacity to transform learning environments is being actively explored by educators, policymakers, and researchers. AI-driven technologies offer adaptive learning systems, real-time analytics, personalised tutoring, and automated feedback, thus redefining pedagogical strategies and enhancing instructional delivery [2, 3]. AI tools such as intelligent tutoring systems, automated essay graders, and learning analytics dashboards are increasingly adopted to optimise learning efficiency, assessment accuracy, and administrative convenience [4-6].

While these developments reflect AI's potential for improving academic performance, much of the existing research remains focused on cognitive or performance-related outcomes, such as academic achievement, knowledge acquisition, and task efficiency [7, 8]. Comparatively fewer studies have investigated AI's role in shaping students' affective experiences and motivational engagement - particularly whether AI can foster greater learning enjoyment [6, 9, 10]. This gap is significant, as emotional engagement is strongly linked to intrinsic motivation, persistence, and deeper learning outcomes [11, 12].

In this study, we conceptualise learning enjoyment not merely as a transient emotional reaction, but as an affective-motivational construct closely aligned with intrinsic motivation, which plays a critical role in sustaining students' interest, curiosity, and commitment to learning [13, 14]. Learning enjoyment reflects the psychological satisfaction derived from engaging with educational tasks, combining both positive emotional experiences and enduring motivational qualities that contribute to deeper learning processes [15]. Thus, investigating how AI influences learning enjoyment offers important insights into students' sustained engagement and long-

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term academic development, rather than merely short-term satisfaction or convenience.

The theoretical foundation of this study integrates the TAM [16] and SDT [13]. While TAM emphasises perceived ease of use and perceived usefulness as drivers of technology adoption [17, 18], SDT emphasises intrinsic motivation driven by autonomy, competence, and relatedness [19-21]. The integration of TAM and SDT allows for a more comprehensive analysis of both the functional and emotional dimensions of AI adoption in higher education [5, 22, 23].

Moreover, as higher education institutions in regions such as the Philippines increasingly adopt AI-powered learning tools [24, 25], it becomes essential to examine not only their technical benefits but also their potential influence on students' affective learning experiences. This study aims to contribute to this emerging discourse by empirically investigating how AI tools affect students' learning enjoyment, using a combined TAM and SDT framework to analyse student attitudes, perceived usefulness, intrinsic motivation, and concerns related to AI use.

2. Methodology

This study employed a descriptive, cross-sectional quantitative design to investigate university students' attitudes towards AI and its role in enhancing learning enjoyment. Grounded in the TAM [16] and SDT [13], the study examined how perceived usefulness, intrinsic motivation, and related constructs influence students' affective engagement with AI tools.

2.1. Sampling procedure and participants

The target population consisted of university students in Regions XI and XII of the Philippines, where the adoption of AI-enabled learning technologies has gradually expanded across public and private institutions. To enhance representativeness, a stratified random sampling technique was employed. Participating institutions were first stratified according to academic discipline (e.g., education, engineering, business, and computer studies) to ensure diversity in academic backgrounds and exposure to AI tools. From these strata, student participants were randomly selected using institutional class lists and electronic enrolment databases provided by the university registrars, ensuring proportional representation across fields of study.

A total of 220 students voluntarily participated in the study during the second quarter of 2025. Participants represented a variety of undergraduate year levels (first year to senior year), with academic majors spanning education (27%), business (22%), information technology/computer science (20%), engineering (18%), and other programmes (13%). The mean age of respondents was 20.8 years (SD=1.9), with a balanced distribution of male (51%) and female (49%) participants. All respondents reported prior exposure to AI tools used in academic settings, including - but not limited to - automated language models, virtual tutors, plagiarism detection systems, personalised learning platforms, and AI-supported research tools.

Recruitment was conducted through institutional email invitations, university bulletin announcements, and instructor referrals during the second quarter of 2025. Participation was voluntary and anonymous, with informed consent obtained prior to data collection. Ethical considerations and protocols adhered to the guidelines set forth by the Philippine Health Research Ethics Board (PHREB).

2.2. Instrumentation and scale development

The survey instrument was developed based on an extensive literature review of students' perceptions and attitudes towards AI [5, 10, 22]. Key constructs reflected performance expectancy, facilitating conditions, ease of use, intrinsic motivation, and enjoyment, drawing from TAM and SDT frameworks [22, 23, 26]. The initial item pool underwent expert validation involving five specialists in educational technology, AI, and psychometric assessment to ensure content validity and construct alignment.

The final instrument consisted of Likert-type items rated on a five-point scale (1=strongly disagree to 5=strongly agree). The scale was pilot-tested prior to full administration to confirm clarity and respondent understanding.

2.3. Data collection and analysis procedures

Data were collected through an online survey distributed via Google Forms over a four-week period. The online format ensured accessibility across multiple campuses and minimised logistical barriers. Descriptive statistics, exploratory factor analysis, and reliability testing were conducted using Jamovi Software 2.0.

Internal consistency reliability was assessed using Cronbach's alpha, yielding values between 0.709 and 0.937 across all subscales [27]. Principal Axis Factoring with a rotation method of Promax with Kaiser Normalization was used. These methods were chosen because an underlying theoretical structure is being hypothesised, and the structure's dimensions or indicators were assumed to be intercorrelated. Construct validity was confirmed via factor analysis. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.948 [28], while Bartlett's Test of Sphericity was significant (χ^2=3623, df=210, p<.001), confirming suitability for factor analysis [29, 30] (Table 1). Factor loadings ranged from 0.414 to 0.946 [31, 32], supporting the stability of the measurement model.

To further assess model adequacy, confirmatory factor analysis and model fit indices were computed, including Chi-square (χ^2=479, df=179, p<.001), CFI=0.916, TLI=0.901, RMSEA=0.0873, and SRMR=0.086, as shown in Table 5, indicating an acceptable model fit [33, 34].

Table 1. KMO and Bartlett's test results.

Bartlett's Test of Sphericity			
χ^2	df	p-value	
3623	210	<.001	
KMO Measure of Sampling Adequacy (MSA)			0.948

3. Results and discussion

In Table 2, Cronbach's alpha coefficients for all scales indicate a strong level of internal consistency, with values ranging from 0.759 to 0.914. This range reflects good to excellent reliability across the constructs assessed [27]. The scale assessing Concerns or Negative Perceptions recorded the lowest reliability (α=0.759); however, despite being the least reliable among the scales, it remains within an acceptable threshold for exploratory research. These reliability coefficients imply that the instruments employed in the study are generally sound and yield dependable measurements of the constructs under examination.

Table 2. Scale reliability statistics.

Scale reliability statistics	Cronbach's α
Perceived enjoyment scale	0.892
Perceived usefulness in learning enjoyment scale	0.906
Social enjoyment in AI-enabled learning scale	0.908
Confidence and control in AI-enabled learning scale	0.914
Concerns or negative perceptions scale	0.759

In Table 3, it is observed that the factor loadings for the majority of items surpass the threshold of 0.7, which is indicative of strong convergent validity. High factor loadings imply that the items are effectively represented by their corresponding factors [35]. The overall factor structure demonstrates that the items maintain a robust connection with their designated constructs, thereby affirming the validity of the measurement model.

Table 4 highlights the ease of understanding and application of the various aspects influencing students' impressions of AI. These factors, including reported happiness, perceived utility, social enjoyment, and

Table 3. Standardised factor loadings from the confirmatory factor analysis.

Factor	Indicator	Estimate	SE	Z	p
Perceived enjoyment	AI tools make studying more fun compared to traditional methods.	0.681	0.0535	12.73	<.001
	Using AI tools in learning makes the experience more enjoyable.	0.733	0.0530	13.83	<.001
	I feel excited when learning with the help of AI-based applications.	0.759	0.0527	14.42	<.001
	Learning with AI motivates me to engage more with course materials.	0.846	0.0564	14.98	<.001
	AI tools provide a more entertaining approach to solving academic problems.	0.702	0.0562	12.49	<.001
Perceived usefulness in learning enjoyment	AI tools help simplify complex topics, making learning more enjoyable.	0.701	0.0553	12.68	<.001
	The use of AI in my studies improves my overall satisfaction with learning.	0.851	0.0550	15.49	<.001
	AI applications help me stay interested in the subject matter.	0.920	0.0586	15.71	<.001
	The interactive features of AI tools make learning less stressful and more enjoyable.	0.711	0.0507	14.02	<.001
	AI tools help me stay focused and entertained during study sessions.	0.809	0.0560	14.45	<.001
Social enjoyment in AI-enabled learning	Collaborating with peers using AI tools enhances my learning enjoyment.	0.781	0.0505	15.48	<.001
	AI tools make group projects more engaging and productive.	0.848	0.0555	15.28	<.001
	Sharing AI-assisted outputs with classmates is an enjoyable experience.	0.835	0.0560	14.92	<.001
	AI applications encourage meaningful discussions with peers during learning activities.	0.814	0.0534	15.25	<.001
Confidence and control in AI-enabled learning	I feel confident and capable when I use AI tools for learning tasks.	0.813	0.0539	15.10	<.001
	AI tools give me more control over my learning process, which I find enjoyable.	0.910	0.0541	16.82	<.001
	I enjoy exploring AI tools because they allow me to learn at my own pace.	0.837	0.0546	15.32	<.001
	Learning with AI gives me a sense of accomplishment and joy.	0.866	0.0577	14.99	<.001
Concerns or negative perceptions	I sometimes find AI tools confusing, which reduces my enjoyment of learning.	0.256	0.0907	2.82	0.005
	I am interested in the development of AI.	0.792	0.0888	8.92	<.001
	Over-reliance on AI tools takes away the creative enjoyment of learning.	0.454	0.0848	5.35	<.001

confidence in AI-enabled learning, are clearly and significantly correlated, according to the data. For instance, a high correlation of 0.875 suggests a particularly strong link between students' enjoyment of AI and their perceptions of its value in education. This indicates that if students enjoy AI-based learning, they are more likely to perceive it as beneficial [35].

However, the correlations between AI-related concerns or unfavourable impressions and other characteristics are marginally weaker, with values ranging from 0.599 to 0.875. This suggests that although unfavourable views are statistically significant, their impact on general attitudes towards AI is smaller than that of the more positive elements [16]. The majority of the components show robust and substantial associations, and the overall factor structure is clear and easy to interpret, allowing academics and educators to use the findings more effectively. As a result, focusing on promoting positive perceptions of AI may help improve students' educational experiences.

The following table includes several statistical measures used to assess the adequacy of the factor analysis concerning respondents' perceptions of AI related to learning enjoyment. These metrics include the chi-square statistic, the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Each of these indices provides important information regarding the overall fit and efficiency of the model.

The chi-square statistic for the model is $\chi^2(179)=479$, $p<.001$, indicating statistical significance. While a large chi-square value typically suggests poor model fit, it is important to note that this statistic is highly sensitive to sample size. In larger samples, the chi-square test often yields significant results even when the model fits the data adequately [36]. Under these considerations, this significant chi-square finding should be interpreted cautiously, as it may reflect the relationship between sample size and the chi-square statistic rather than a substantial discrepancy between the observed and expected covariance matrices.

The CFI is 0.916, and the TLI is 0.901, with both exceeding the commonly accepted minimum threshold of 0.90. These results indicate an overall marginal model fit. Both indices compare the proposed model against a baseline model and suggest that the model adequately explains the relationships among the observed variables [33]. The values of the CFI and TLI therefore support the appropriateness of the model structure for the data.

The RMSEA is estimated at 0.0873, with a 90% confidence interval ranging from 0.0779 to 0.0968. This

Table 4. Latent factor correlation matrix.

Factor	Indicator	Estimate	SE	Z	p
Student attitudes towards AI in terms of perceived enjoyment	Student attitudes towards AI in terms of perceived enjoyment	1.00			
	Student attitudes towards AI in terms of perceived usefulness in learning enjoyment	0.875	0.0245	35.76	<.001
	Student attitudes towards AI in terms of social enjoyment in AI-enabled learning	0.865	0.0257	33.68	<.001
	Student attitudes towards AI in terms of confidence and control in AI-enabled learning	0.802	0.0319	25.13	<.001
	Student attitudes towards AI in terms of concerns or negative perceptions	0.607	0.0691	8.79	<.001
Student attitudes towards AI in terms of perceived usefulness in learning enjoyment	Student attitudes towards AI in terms of perceived usefulness in learning enjoyment	1.000			
	Student attitudes towards AI in terms of social enjoyment in learning enjoyment	0.843	0.0272	31.01	<.001
	Student attitudes towards AI in terms of confidence and control in AI-enabled learning	0.854	0.0254	33.63	<.001
	Student attitudes towards AI in terms of concerns or negative perceptions	0.633	0.0709	8.93	<.001
Student attitudes towards AI in terms of social enjoyment in AI-enabled learning	Student attitudes towards AI in terms of social enjoyment in AI-enabled learning	1.000			
	Student attitudes towards AI in terms of confidence and control in AI-enabled learning	0.843	0.0253	34.12	<.001
	Student attitudes towards AI in terms of concerns or negative perceptions	0.612	0.0678	9.03	<.001
Student attitudes towards AI in terms of confidence and control in AI-enabled learning	Student attitudes towards AI in terms of confidence and control in AI-enabled learning	1.000			
	Student attitudes towards AI in terms of concerns or negative perceptions	0.599	0.0674	8.89	<.001
Student attitudes towards AI in terms of concerns or negative perceptions	Student attitudes towards AI in terms of concerns or negative perceptions	1.000			

value is slightly above the generally accepted threshold of 0.08, indicating a moderate fit. Although the RMSEA suggests that the model does not perfectly represent the population covariance structure, it remains close to the acceptable limit, implying that the model can still be regarded as reasonably fitting. Moreover, the lower bound of the confidence interval falls below 0.08, suggesting that the model fit may be considered marginally acceptable.

The SRMR is reported as 0.086, which marginally exceeds the recommended threshold of 0.08 adopted by L. Hu, et al. (1999) [33]. This indicates that the model is close to achieving an acceptable fit but may benefit from minor refinements. The SRMR reflects the standardised difference between observed and predicted correlations. Although values above 0.08 suggest a suboptimal fit, an SRMR of 0.086 still indicates a reasonably good model fit, and further adjustments could improve congruence with the observed data.

The model fit statistics indicated a satisfactory fit. CFI and TLI were good indicators that the model fitted the data well, although RMSEA and SRMR were slightly above the commonly recommended cut-offs, indicating marginal model fit [34]. The values being somewhat higher for RMSEA and SRMR suggest that further refinements of the models of certain elements or items whose low factor loadings could be contributing to the marginal fit.

Table 5. Confirmatory factor analysis model-fit indices.

Test for exact fit					
χ^2	df	p			
479	179	<.001			
Comparative Fit Index	Tucker-Lewis Index	Root Mean Square Error of Approximation	Standardised Root Mean Square Residual	Lower	Upper
0.916	0.901	0.0873	0.086	0.0779	0.0968

RMSEA 90% CI.

3.1. Level of students' attitudes towards artificial intelligence

Tables 6-10 presented below illustrate the average scores concerning respondents' perceptions of AI in relation to learning enjoyment, derived from the analysis of 220 completed responses. In general, respondents demonstrate a moderately favourable attitude towardss the integration of AI in educational contexts, reflected by an average score of Mean=3.60 (SD=0.671). This finding suggests that respondents predominantly regard AI as a beneficial resource for improving learning enjoyment, albeit with some degree of variability in individual opinions.

Analysing the data in more detail, the subscale measuring Perceived Usefulness in Learning Enjoyment achieved the highest score, with a mean of 3.67 (SD=0.838). This indicates that respondents perceive AI as especially advantageous in enhancing their enjoyment of the learning process [6]. Such a finding underscores a favourable view of AI's ability to enrich the educational experience. Nonetheless, the higher standard deviation points to a wider range of opinions among respondents, suggesting that the perceived benefits of AI vary significantly among individuals [37].

Conversely, the Concerns or Negative Perceptions subscale, which has a mean score of 3.55 (SD=0.760), indicates a relatively elevated level of apprehension regarding the use of AI in educational settings. While the score remains moderately positive, it underscores that certain respondents exhibit a more cautious or sceptical stance towardss the integration of AI in education. The moderate standard deviation observed in this subscale further implies a diversity of opinions concerning the possible disadvantages or challenges linked to the application of AI in learning environments [38].

Overall, the findings indicate a predominantly favourable perspective on the application of AI in educational settings, although there is notable variability in respondents' attitudes, particularly with respect to its perceived utility and associated concerns. This suggests that while the majority view AI as advantageous, there are considerable apprehensions that must be addressed to facilitate wider acceptance.

Table 6. Student attitudes towardss AI in terms of perceived enjoyment.

Statements	N	Mean	SD
AI tools make studying more fun compared to traditional methods.	220	3.86	0.906
Using AI tools in learning makes the experience more enjoyable.	220	3.65	0.921
I feel excited when learning with the help of AI-based applications.	220	3.56	0.932
Learning with AI motivates me to engage more with course materials.	220	3.55	1.012
AI tools provide a more entertaining approach to solving academic problems.	220	3.74	0.951
Grand Mean	220	3.67	0.790

Table 6 further indicates that respondents display a favourable attitude towardss the enjoyment associated with AI, with mean scores ranging from 3.55 to 3.86. This finding implies a generally positive perception of the enjoyable features of AI, as evidenced by the relatively low variability in respondents' responses (Grand Mean=3.64, SD=0.790).

Furthermore, consistent with the research by A.R. Malik, et al. (2023) [8] on AI in education, students show a positive disposition towardss the incorporation of AI into their academic endeavours. The results reveal a strong recognition among respondents of the potential advantages offered by AI tools. Based on the feedback received, AI is regarded as a valuable asset that provides significant benefits, thereby enhancing students' educational experiences.

Table 7. Student attitudes towardss AI in terms of perceived usefulness in learning enjoyment.

Statements	N	Mean	SD
AI tools help simplify complex topics, making learning more enjoyable.	220	3.89	0.942
The use of AI in my studies improves my overall satisfaction with learning.	220	3.63	1.001
AI applications help me stay interested in the subject matter.	220	3.56	1.073
The interactive features of AI tools make learning less stressful and more enjoyable.	220	3.82	0.893
AI tools help me stay focused and entertained during study sessions.	220	3.46	0.955
Grand Mean	220	3.67	0.838

In Table 7, the data indicate a favourable tendency among respondents to acknowledge the perceived benefits of AI in enhancing the enjoyment of learning. This is demonstrated by their expressed intentions to increase interest, motivation, and engagement in the educational process, with mean scores ranging from 3.46 to 3.89. Respondents not only recognise the significance of AI but also exhibit a proactive approach to incorporating AI tools to enhance their learning experiences, thereby making the learning process more enjoyable and engaging (Grand Mean=3.67, SD=0.838).

This favourable tendency is consistent with the findings of N.N. Ayoub, et al. (2024) [39], which emphasise a distinctly positive attitude towardss the integration of AI as a valuable resource for improving learning enjoyment. In addition, further research highlights the role of AI in enhancing learning experiences by rendering them more engaging and enjoyable [3, 40]. The positive responses from respondents - encompassing perceptions of usefulness, ease of use, and overall satisfaction - collectively indicate a promising future for AI tools in enriching students' educational journeys.

Table 8. Student attitudes towardss AI in terms of social enjoyment in AI-enabled learning.

Statements	N	Mean	SD
Collaborating with peers using AI tools enhances my learning enjoyment.	220	3.50	0.919
AI tools make group projects more engaging and productive.	220	3.66	1.005
Sharing AI-assisted outputs with classmates is an enjoyable experience.	220	3.54	1.004
AI applications encourage meaningful discussions with peers during learning activities	220	3.43	0.965
Grand Mean	220	3.53	0.862

In Table 8, the data indicate a favourable disposition among respondents regarding the social enjoyment associated with AI-enabled learning, with mean scores ranging from 3.43 to 3.67. This suggests that students generally perceive AI-enabled learning as socially engaging and enjoyable. The relatively low variability in responses further implies a uniform understanding of AI's capacity to improve social interaction within educational settings (Grand Mean=3.53, SD=0.862).

Notably, research conducted by Z. Xu (2024) [40] and P. Kaledio, et al. (2024) [3] supports these findings, demonstrating that AI-enabled learning tools can significantly enhance students' educational experiences. These tools are crucial in promoting social interaction, boosting engagement, and facilitating collaboration among students, thereby creating a more vibrant and enjoyable learning atmosphere. This alignment of participant perceptions underscores the potential of AI to enrich the social dimensions of learning and highlights its significance as an effective instrument for improving student engagement and interaction.

Table 9. Student attitudes towardss AI in terms of confidence and control in AI-enabled learning.

Statements	N	Mean	SD
I feel confident and capable when I use AI tools for learning tasks.	220	3.50	0.972
AI tools give me more control over my learning process, which I find enjoyable.	220	3.49	1.018
I enjoy exploring AI tools because they allow me to learn at my own pace.	220	3.62	0.992
Learning with AI gives me a sense of accomplishment and joy.	220	3.45	1.039
Grand Mean	220	3.51	0.896

In Table 9, the data reveal that respondents exhibit a favourable disposition regarding their confidence and sense of control in AI-assisted learning, with mean scores ranging between 3.45 and 3.62. This suggests that students predominantly feel empowered and assured when utilising AI tools in their educational activities. Additionally, the limited variation in responses implies a relatively uniform belief in AI's capacity to enhance students' sense of control and self-confidence in their learning experiences (Grand Mean=3.51, SD=0.896).

Research conducted by N.D. Bation, et al.(2024) [22] supports these results by emphasising that students' confidence and perceived control in AI-enabled learning environments play a critical role in shaping their overall attitudes towardss AI. The findings indicate that students are more likely to engage favourably with AI technologies when they feel comfortable using them and believe that they retain control over their learning processes. Moreover, higher levels of self-efficacy are associated with a stronger sense of ownership over educational activities. As AI tools have the potential to strengthen students' agency and efficacy in the learning process, the alignment between the study's findings and prior research underscores the importance of fostering confidence and control in AI-enabled learning environments.

Table 10. Student attitudes towards AI in terms of concerns or negative perceptions.

Statements	N	Mean	SD
I sometimes find AI tools confusing, which reduces my enjoyment of learning.	220	3.11	1.094
I am interested in the development of AI.	220	3.82	0.995
Over-reliance on AI tools takes away the creative enjoyment of learning.	220	3.70	1.038
Grand Mean	220	3.55	0.760

Based on the data presented in Table 10, the results attest that there is a degree of fear or negative perception towards AI, with mean scores ranging between 3.11 and 3.82. Thus, although many respondents express some level of caution or scepticism regarding AI, the overall sentiment remains relatively balanced. The low variation in responses reflects a general equilibrium in respondents' levels of concern, indicating that students tend to feel either mildly worried or largely neutral about the role of AI in education (Grand Mean=3.55, SD=0.76).

Most respondents adopt a neutral stance towards AI, which supports this balanced perspective. A. Smolansky, et al. (2023) [41] explain that such average scores suggest that some students may have concerns about how AI could affect education, but these concerns are not particularly strong. The responses are relatively homogeneous, with most students expressing similar views, as reflected by the standard deviation of 0.760. This pattern suggests that students are cautious or somewhat uncertain, yet not polarised in their opinions, and are likely to approach AI in education with careful optimism rather than outright rejection [42].

Despite generally positive attitudes towards AI, participants reported meaningful concerns about over-reliance on AI tools (M=3.70) and the over-reliance and loss of creative enjoyment (M=3.70). Such concerns align with growing debates in the literature suggesting that excessive automation may undermine critical thinking, originality, and learner autonomy if not carefully managed [41, 42]. Students' confusion when using AI tools (M=3.11) also indicates usability challenges that could create frustration or disengagement if interfaces are not designed to support intuitive learning experiences. These concerns suggest that, while AI can enhance learning enjoyment, poorly designed systems or excessive dependence may paradoxically reduce students' creative ownership of learning, potentially limiting long-term skill development.

3.2. Group differences (independent samples t-test)

Gender-based comparisons indicated minor differences, with male students reporting slightly higher learning enjoyment scores than female students (M_male=3.71, SD=0.72; M_female=3.48, SD=0.59). However, the observed effect sizes in Table 11 (Cohen's d=-0.336; r=0.237) and significance levels suggest that these differences are small and may not hold substantial practical significance [43, 44] (Table 12). Accordingly, these gender differences should be interpreted with caution.

Table 11. Gender differences in overall AI-attitude scores.

		Statistic	df	p	Mean difference	SE difference		Effect size
Grand Mean	Student's t	-2.49	218	0.014	-0.223	0.0894	Cohen's d	-0.336
	Mann-Whitney U	4614		0.002	-0.258		Rank biserial correlation	0.237

H_a $\mu_{Female} \neq \mu_{Male}$.

Table 12. Group descriptions.

	Group	N	Mean	Median	SD	SE
Grand Mean	Female	107	3.48	3.45	0.592	0.0572
	Male	113	3.71	3.72	0.723	0.0680

3.3. Theoretical implications

This study also contributes to the existing body of knowledge on the use of artificial intelligence in educational settings by combining two major models: the TAM [16] and SDT [13]. The theoretical implications of this research are manifold, with one of the main contributions being the further development of existing theories of technology use, as well as an enhanced understanding of how intrinsic motivation affects learners' perceptions of AI-based instructional tools [15].

This study reaffirms the significance of students' attitudes towards AI as a crucial factor influencing their intention to utilise AI technologies, in accordance with TAM. The findings indicate that students are more inclined to adopt AI tools when they perceive them as both beneficial and user-friendly [17]. This observation highlights the continuing importance of TAM and SDT as key determinants of technology adoption, particularly in the context of AI [18]. By validating the relevance of TAM within higher education environments, this research strengthens the model's capacity to predict students' behavioural intentions regarding the adoption of innovative educational technologies [45]. However, the findings also highlight the need for a deeper understanding of these behavioural attitudes and their influence on the actual use of AI applications. In this regard, both TAM and SDT present inherent limitations in fully explaining students' AI learning behaviour. TAM primarily emphasises perceived usefulness and ease of use but does not sufficiently account for broader contextual and social influences such as peer interaction, instructor support, institutional conditions, and technological infrastructure, which are critical in AI-enabled learning environments. It also assumes relatively rational decision-making and may overlook emotional, ethical, and critical responses to AI use. Meanwhile, SDT offers insights into intrinsic motivation through autonomy, competence, and relatedness but does not adequately address technology-specific issues such as the reliability, accuracy, and transparency of AI systems, nor learners' trust in algorithmic outputs. Additionally, SDT may not fully capture the tension between enhanced autonomy and potential over-reliance on AI, which could undermine creativity and deep learning, suggesting the need for integrating additional perspectives that consider social, technological, and trust-related factors.

Incorporating SDT into the analytical framework highlights the psychological factors associated with the transition towardss the use of artificial intelligence and thus comprehensively shows how the students are engaged. It is very well possible that students' motivation to use AI tools may be fostered by these tools' capacity to satisfy psychological needs for autonomy, competence, and relatedness. AI systems that support personalised learning pathways can enhance autonomy, provide timely feedback to strengthen competence, and facilitate interaction to promote social connectedness, thereby encouraging learners to become more intrinsically motivated to engage with technology [19]. This is particularly significant in academic contexts, where motivation is closely linked to sustained engagement and academic success. However, while SDT offers valuable insights into motivational processes, it does not fully account for technology-specific concerns inherent in AI use. In particular, SDT cannot adequately explain issues related to the reliability and accuracy of AI-generated information, the quality and biases of underlying algorithms, or students' trust in AI outputs. These factors may significantly influence learners' willingness to engage with AI tools beyond motivational considerations alone. Thus, while focusing on motivational aspects of AI adoption is appropriate, it is not sufficient on its own, and a more comprehensive framework is needed to capture both psychological and technological dimensions of AI use.

The integration of TAM and SDT further reinforces the argument that perceptions of AI in education extend beyond ease of use and perceived usefulness [20]. It also accounts for how effectively AI technologies respond to students' fundamental psychological needs. This integrated theoretical framework offers a more nuanced understanding of AI adoption, highlighting the complex interactions between cognitive perceptions and underlying motivational processes.

4. Conclusions

This study examined the attitudes of university students towards AI and how these attitudes shape their perceptions and, consequently, influence AI adoption in education. By integrating TAM and SDT, the study presents a meaningful framework for understanding the factors driving AI adoption. The findings reveal that students' perceptions of the usefulness and ease of use of AI are significant determinants of their willingness to adopt it. The study also indicates that intrinsic motivation - specifically autonomy, competence, and relatedness - plays a role in AI adoption, as inferred from SDT. However, it is important to acknowledge that TAM does not fully account for the influence of external and contextual factors such as peer interaction, instructor support, and technological conditions (e.g., access to devices and internet connectivity), which may significantly shape students' engagement with AI in educational settings. These facilitating conditions suggest that AI adoption not is solely an individual cognitive evaluation but is also socially and institutionally mediated. Furthermore, while most students reported positive experiences with AI, they also expressed negative perceptions regarding certain attributes of AI, warranting further investigation. It was found that male students generally exhibited more positive attitudes towards AI, indicating gender differences in how individuals interact with AI tools. The results further suggest that improvements to the measurement model are needed, as reflected by the mediocre RMSEA value and weak item loadings.

In effect, the study contends that AI adoption in higher education is influenced by both functional benefits and emotional appeal. In this regard, institutions should place greater emphasis on developing AI tools that nurture autonomy, competence, and relatedness, rather than focusing solely on technical aspects of use. Future studies should examine how these factors influence learning outcomes as AI technologies continue to evolve.

5. Recommendations

The findings of this study indicate that the integration of AI into higher education should address not only technological capacity but also students' psychological engagement. Institutions may design AI-enhanced learning environments that actively support intrinsic motivation by fostering autonomy, competence, and relatedness through personalised pacing, adaptive feedback, and collaborative learning experiences. However, given the reported concerns regarding over-reliance on AI and diminished creativity, educators should deliberately integrate AI as a complement to, rather than a replacement for, active, critical, and creative learning tasks.

To mitigate potential drawbacks, faculty development programmes may be implemented to equip instructors with the pedagogical skills needed to integrate AI tools thoughtfully into instructional design. These programmes may include strategies for balancing automation with opportunities for student-led inquiry, problem-solving, and creative production, ensuring that students remain cognitively engaged rather than passively dependent on AI-generated outputs.

At the policy level, institutions may develop clear ethical guidelines for AI use, addressing issues such as data privacy, algorithmic transparency, and responsible reliance on AI-generated content. Students should also receive training in digital literacy and critical engagement with AI, enabling them to evaluate AI outputs, understand algorithmic limitations, and make informed decisions when using AI-supported platforms. Integrating AI literacy modules into general education curricula may help foster responsible and reflective AI use early in students' academic journeys.

Finally, given the variability in attitudes across academic disciplines and the minor gender-based differences identified in this study, future research may employ multi-group analyses to explore how different learner profiles experience AI integration. Tailoring AI-supported pedagogical approaches to specific student needs may further enhance learning enjoyment and academic outcomes while addressing diverse expectations in higher education contexts.

6. Limitations and future research

This study has several limitations that should be considered when interpreting the findings.

First, although grounded in TAM and SDT, the study did not examine additional factors such as social influence, trust in AI, or prior AI experience, which may further shape students' attitudes and usage behaviours. Moreover, the cross-sectional design captures perceptions at a single point in time; future longitudinal studies are needed to examine how students' motivations and attitudes evolve with increased exposure to AI tools.

Second, the sample was limited to university students from selected regions of the Philippines, which restricts the generalisability of the findings across educational levels, disciplines, and cultural contexts. Broader and more diverse samples would allow for a more comprehensive understanding of how AI adoption varies across learner populations and institutional environments. Additionally, institutional and technological factors - such as internet access, device availability, and organisational support - were not directly measured, despite their potential influence on students' engagement with AI-based learning systems.

Finally, although the measurement model demonstrated acceptable fit, the slightly elevated RMSEA (0.0873) and SRMR (0.086) values suggest minor model misfit, potentially attributable to weaker item loadings within the Concerns or Negative Perceptions subscale. Refining these items and exploring alternative modelling strategies, such as item parcelling, may improve measurement precision in future research.

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COMPETING INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this article.

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