Adoption of AI Tools for Learning: A Tpb-Tam Integrated Model with FOMO as a Moderator- A Case Study at Hanoi University of Science and Technology (HUST)

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Abstract
Research purpose:
This study examines the behavioral intention and actual usage of AI-powered learning tools among university students by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), with Fear of Missing Out (FOMO) included as a moderating factor.
Research motivation:
While AI tools are increasingly adopted in education, there is limited understanding of how behavioral and technological factors jointly influence their use, especially in the Vietnamese higher education context. This research addresses this gap, focusing on Hanoi University of Science and Technology (HUST), a leading institution in science and technology education in Vietnam.
Research design, approach, and method:
Data were collected from 409 undergraduate students through a structured survey. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the proposed hypotheses.
Main findings:
The results indicate that perceived behavioral control, subjective norms, and attitude toward AI tools significantly predict students' behavioral intention, whereas perceived enjoyment and computer self-efficacy do not. Behavioral intention positively influences actual usage, and FOMO strengthens the relationship between intention and behavior.
Practical/managerial implications:
The findings highlight the dominance of utilitarian over hedonic motivations in AI adoption for learning. Educators, universities, and AI developers should prioritize functionality, accessibility, and social influence factors over enjoyment to enhance technology adoption in educational settings.
Keywords: Artificial intelligence (AI); TAM; TPB; Fear of missing out (FOMO); AI tool adoption; higher education.

1. INTRODUCTION

As digital transformation accelerates worldwide, artificial intelligence (AI) tools are gaining increasing significance in higher education. Their integration into teaching and learning not only enhances personalized learning experiences but also broadens access to diverse resources and nurtures future-ready skills. In Vietnam, especially at technically oriented institutions such as Hanoi University of Science and Technology (HUST), AI adoption for educational purposes is emerging. However, the underlying behavioral dynamics driving AI tool usage remain underexplored.

Despite the growing availability of AI-based learning applications, most earlier research has focused mainly on their perceived usefulness and user-friendliness (Davis, 1989), often neglecting complex psychological factors that may influence student adoption (Nguyen et al., 2023; Van Le et al., 2021). These include social influence, individual competencies, and hedonic motivations. To address this gap, the present study combines the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) to analyze how psychological and behavioral factors shape students' willingness to engage with AI technologies. Specifically, it explores the mediating role of behavioral intention that connects perceived behavioral control, perceived enjoyment, attitude toward AI, and actual usage behavior.

A notable extension of this research is the inclusion of Fear of Missing Out (FOMO), which refers to the unease people feel when they perceive themselves as excluded from valuable experiences or information (Przybylski et al., 2013). In digitally connected university environments where AI use is becoming the norm (Steinbauer et al., 2021), students may feel compelled to adopt AI tools not merely for practical benefits but to keep up with peers. Among Vietnamese students, particularly Gen Z learners who are inherently tech-savvy, FOMO may reinforce the connection

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between intention and actual usage. Therefore, this study investigates FOMO as a moderating factor, offering a more nuanced understanding of AI adoption in education. As one of Vietnam's top technical universities, HUST has rapidly embraced digital transformation and actively integrates AI tools into its learning management system (LMS). While the institution encourages both instructors and students to experiment with AI for learning and research, successful implementation depends not only on technological infrastructure but also on students' psychological readiness and behavioral tendencies. Accordingly, the research sets out to: (1) Determine principal antecedents that shape students' intentions and behaviors regarding AI tool usage; (2) Assess the moderating influence of FOMO on the pathway from intention to actual usage; (3) Offer practical recommendations for educators, AI developers, and university administrators to enhance AI integration strategies while supporting students' psychological well-being.

2. LITERATURE REVIEW

2.1. The research background and theoretical framework

A Synthesized Approach Using TPB and TAM

This study employs an integrated framework combining the TPB and TAM to investigate students' adoption of AI-based learning tools. TPB provides a behavioral lens by explaining how individuals' intentions to perform a behavior are influenced by attitudes, perceived social pressure, and and their sense of control over performing it (Ajzen, 1991). In the educational setting, TPB has been applied to understand student decisions by emphasizing how personal beliefs and social pressures influence learning-related behaviors.

In parallel, TAM serves as a foundational model for exploring technology adoption, emphasizing perceived usefulness (PU) and perceived ease of use (PEOU) as major factors shaping attitudes and intentions (Davis, 1989). TAM has been extensively applied in digital education to understand how students and educators respond to emerging technologies, including AI-based applications. By integrating TPB and TAM, this approach develops a multidimensional view of both the psychological and technological factors driving students' behavior. The combined model accounts not only for perceived utility and usability but also for social norms and individual control, which are essential in explaining behavioral intentions in a digitally evolving educational environment.

2.2. Conceptual Definitions and Hypothesis Development

Perceived Behavioral Control and AI Adoption Intention

Perceived behavioral control (PBC) reflects how capable individuals feel in performing a behavior, considering possible barriers or enablers (Ajzen, 1991; Troise et al., 2021). In education, PBC indicates students' belief in their capacity to utilize AI tools proficiently, even when facing technical or resource-related challenges. When students feel supported and prepared, their intention to adopt such tools strengthens (Kucuk et al., 2020). Based on these arguments, the study proposes that:

H1: PBC positively influences students' intentions to adopt AI-powered learning tools.

Subjective Norms and AI Adoption Intention

Subjective norms (SN) reflect the sense of normative pressure to engage in a specific action, based on the expectations of influential figures like peers, family, or educators (Ustadi & Mat, 2023). In academic environments, learners tend to embrace AI technologies when they perceive endorsement or encouragement from their social circle (Hussein, 2018). Accordingly, this study suggests:

H2: Subjective norms positively affect students' intention to utilize AI-powered learning tools.

Perceived enjoyment and AI adoption intention

Perceived enjoyment (PE) reflects the intrinsic satisfaction users experience when engaging with a technology for its own sake, rather than for functional outcomes (Hussein, 2018). In education, when students find learning tools enjoyable and appealing, they show stronger willingness to adopt (Roslan et al., 2021). Enjoyment enhances user motivation and fosters greater acceptance of digital platforms. Hence, this study proposes:

H3: Perceived enjoyment positively influences students' intention to adopt AI-powered learning tools.

Computer self-efficacy and AI adoption intention

Computer self-efficacy (CS) reflects students' belief in their competence to handle digital technologies efficiently. When learners believe they can operate AI-powered technologies with competence, they are more likely to adopt them (Simsek, 2011; Nurhikmah et al., 2021). Conversely, limited confidence may hinder acceptance. Prior research affirms the positive relationship between CS and technology use across educational platforms (Hayashi et al., 2004). Thus, the hypothesis is formulated as follows:

H4: Computer self-efficacy positively influences students' intention to adopt AI-powered tools.

Attitudes and Behavioral Intentions Toward AI Use

Attitudes toward behavior refer to a student's overall evaluation, whether positive or negative, of using AI tools in learning (Ajzen, 1991). When students anticipate beneficial outcomes from engaging with such technologies, they tend to form more positive evaluations. These attitudes, in turn, contribute to stronger behavioral intentions

(Ustadi & Mat, 2023). This association has been consistently observed across a range of digital and sustainability-related contexts. Accordingly, this study posits:
H5: Students' positive attitudes significantly influence their intention to use AI-powered tools.

Users' perceptions of usefulness, usability, and attitudes toward AI tools

Perceived usefulness (PU) and perceived ease of use (PEOU) are foundational elements of the Technology Acceptance Model (TAM), both playing essential roles in shaping users' attitudes toward technology (Davis, 1989). PU captures the extent to which students view AI technologies as beneficial for optimizing academic achievement by improving task efficiency and learning performance (Saparudin et al., 2020). Meanwhile, PEOU relates to the perceived simplicity and user-friendliness of a system, which also fosters favorable attitudes when users believe minimal effort is required (Naeem et al., 2023). Positive attitudes, in turn, strongly influence individuals' intentions to adopt technology. Both the TAM and TPB assert that intention serves as the closest determinant of actual behavior, serving as a reliable indicator of whether a person will engage with a given system (Wang et al, 2022). Therefore, based on these relationships, the following hypotheses are proposed:
H6: Perceived usefulness positively influences students' attitudes toward using AI-powered tools.
H7: Perceived ease of use positively influences students' attitudes toward using AI-powered tools.
H8: Behavioral intention positively influences students' actual use of AI-powered tools.

The moderating role of FOMO in the relationship between behavioral intention and actual use of AI tools

Fear of Missing Out (FOMO) refers to a psychological condition involving anxiety that others are enjoying experiences without one's participation (Przybylski et al., 2013). In digitally connected educational environments, especially where AI adoption is increasingly normalized, FOMO can act as a significant driver of behavior. Individuals experiencing high levels of FOMO often seek to stay updated and engaged to avoid being left behind socially or academically (Kuss & Griffiths, 2017). While the TPB and TAM suggest that behavioral intention is the most primary driver leading to actual behavior (Ajzen, 1991; Davis, 1989), the strength of this relationship may be influenced by individual psychological traits. FOMO, acting as a motivational trigger, may encourage students to promptly act on their intentions to avoid missing potential learning advantages. Based on this reasoning, the study articulates the following hypothesis:

H9: FOMO significantly moderates the relationship between behavioral intention and the actual use of AI-powered tools.

The theoretical model below is informed by prior empirical findings and the hypotheses proposed in this study:

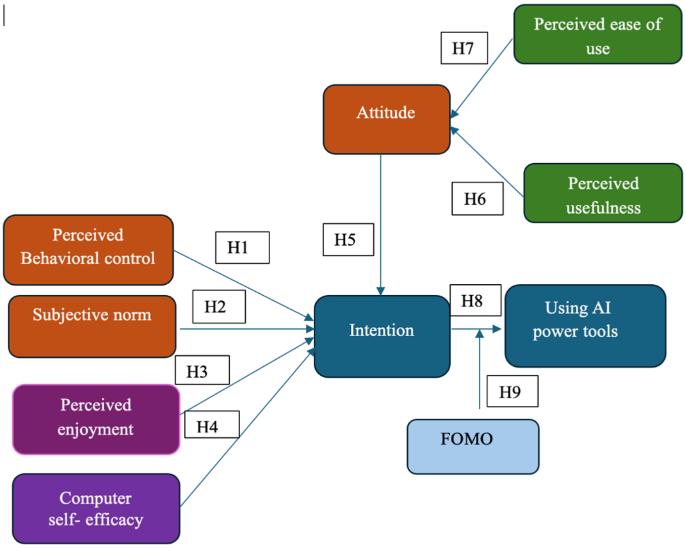

Fig. 1. Theoretical framework

3. METHODOLOGY

3.1. Sample and data collection

This study employed a convenience sampling method to collect data from undergraduate students at Hanoi University of Science and Technology (HUST), aligning with the research aim of examining students' perceptions and behaviors regarding the use of AI-driven educational technologies within university settings. According to Bollen (1989), for Structural Equation Modeling (SEM), the minimum suggested sample size is fivefold the number of observed indicators. Given the 36 measurement items in the model, the required minimum sample size was 180 participants. To enhance statistical reliability, the study aimed to exceed this threshold.

Data were gathered across a two-month span between March and May 2025, resulting in 409 valid responses. To enhance the reliability of the responses, each participant was restricted to a single submission via Google Forms, using access settings that prevented multiple entries from the same individual.

Table 1. Demographic characteristics of participants

Characteristics	Number (n)	Percentage (%)
Total	409	100
Gender		
Male	206	50.4
Female	197	48.2
Other	6	1.5
Study Year		
Year 1	85	20.8
Year 2	138	33.7
Year 3	155	37.9
Year 4	25	6.1
Year 5	5	1.2
Other	1	0.2
CPA		
<2.0	14	3.4
2.0 -2.49	40	9.8
2.5 - 3.19	193	47.2

Characteristics	Number (n)	Percentage (%)
3.2 - 3.59	115	28.1
3.6 - 4.0	47	11.5
Major		
Economics	175	42.8
Foreign languages	31	7.6
Engineering	164	40.1
Education	38	9.3
Other	1	0.2

3.2. Measurement

The measurement items in this study were derived from previously validated scales. Perceived usefulness (PU) was measured by 4 items adapted from Davis (1989) and Fathema et al. (2015). Perceived ease of use (PEOU) was assessed using 4 items adapted from Davis (1989) and Salloum et al. (2019) to evaluate the perceived simplicity of AI tool usage in academic tasks. Perceived behavioral control (PBC) consisted of 5 items from Taylor & Todd (1995), measuring students' perceived ability to control their use of AI tools. Perceived enjoyment (PE) was captured by 3 items derived from Salloum et al. (2019), assessing the degree of enjoyment experienced by students when engaging with AI- based educational tools. Attitude toward use (ATU) included 5 items from Fathema et al. (2015) to evaluate learners' evaluative orientation regarding the use of AI tools. Subjective norm (SN) was assessed through three indicators from Salloum et al. (2019) to capture the influence of social pressure from peers, instructors, and family. Computer self-efficacy (CS) was assessed through 3 items adopted from Fathema et al. (2015), evaluating students' confidence in using digital technology. Behavioral intention (BI) was measured with 3 items based on Fathema et al. (2015) and Salloum et al. (2019), reflecting students' intent to adopt AI-powered tools. Actual Behavior (AB) was measured by 3 items referenced from Göncz & Tian (2020), reflecting students' real usage behavior. Fear of Missing Out (FOMO) was assessed with 4 items adapted from Ng et al. (2023), capturing the psychological fear of being left out of technological trends.

In total, the final questionnaire comprised 36 items, each rated on a five-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). To establish content adequacy, the original English items were translated into Vietnamese and then back-translated by bilingual experts to ensure semantic consistency. A pilot survey was carried out to verify the comprehensibility and suitability of the questionnaire items prior to full-scale data collection.

3.3. Data analysis

This study employed structural equation modeling (SEM) using the Partial least squares (PLS-SEM) technique to examine the proposed conceptual framework. PLS-SEM was selected due to its flexibility regarding data distribution assumptions and suitability for both small and large sample sizes (Hair et al., 2019). It is particularly appropriate for predictive modeling and theory development in social science research (Peng & Lai, 2012).

The analysis followed a two-stage procedure: (1) analysis of the measurement components , and (2) validation of hypothesized paths (Henseler et al., 2009). The measurement model was assessed for indicator reliability, construct reliability, convergent validity, and discriminant validity. Indicator loadings of 0.7 or above were considered satisfactory (Hair et al., 2019), while Cronbach's Alpha and Composite Reliability (CR) values above 0.7 confirmed internal consistency (Henseler & Sarstedt, 2013). Convergent validity was verified via Average Variance Extracted (AVE) thresholds above 0.5 (Ringle et al., 2020). The Fornell-Larcker criterion and HTMT index were employed to verify discriminant validity, with HTMT values under 0.90 (Henseler et al., 2015). The structural model was evaluated through a bootstrapping procedure with 5,000 resamples to determine the statistical significance of path estimates. Additional assessments included multicollinearity (using VIF) and explanatory power (R^2), in line with recommendations by Hair Jr et al. (2021).

4. RESULTS

4.1. Measurement model

Initially, the outer loadings of the observed variables were examined. Indicators with loadings below 0.7 were deemed insufficient in representing their respective constructs and were thus excluded. After this adjustment, all remaining indicators demonstrated loadings above 0.7, indicating their strong contribution to the measurement model (Table 2).

Table 2. Outer Loadings (Second Iteration)

	AB	ATU	BI	CS	FM	PBC	PE	PEOU	PU	SN
AB1	0.876									
AB2	0.911									
AB3	0.850									
ATU1		0.838								
ATU2		0.836								
ATU3		0.860								
ATU4		0.781								
ATU5		0.868								
BI1			0.902							
BI2			0.913							
BI3			0.892							
CS1				0.851						
CS2				0.879						
CS3				0.738						
FM1					0.889					
FM2					0.868					
FM3					0.915					
FM4					0.907					
PBC1						0.877				
PBC2						0.741				
PBC4						0.792				
PE1							0.839			
PE2							0.869			
PE3							0.847			
PEOU1								0.824		
PEOU2								0.833		
PEOU3								0.741		
PEOU4								0.825		
PU1									0.836	
PU2									0.852	
PU3									0.907	
PU4									0.883	
SN2										0.903
SN3										0.900

As presented in Table 3, the Cronbach's alpha values range between 0.804 and 0.913, and Composite Reliability (CR) values fall between 0.812 and 0.936, all surpassing the recommended threshold of 0.7, thus confirming internal consistency. Additionally, the AVE values, which range from 0.558 to 0.830, exceed the 0.5 benchmark, supporting the model's convergent validity.

Table 3. Construct Reliability, Convergent Validity (Second Iteration)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AB	0.853	0.855	0.911	0.774
ATU	0.893	0.899	0.921	0.701
BI	0.886	0.886	0.929	0.815
CS	0.762	0.768	0.864	0.681
FM	0.917	0.919	0.942	0.801
PBC	0.731	0.769	0.846	0.649
PE	0.814	0.828	0.888	0.725

PEOU	0.820	0.826	0.881	0.651
PU	0.892	0.893	0.925	0.756
SN	0.770	0.771	0.897	0.813

Table 4. Fornell- Lacker Criterion (Second Iteration)

	AB	ATU	BI	CS	FM	PBC	PE	PEOU	PU	SN
AB	0.880									
ATU	0.631	0.837								
BI	0.648	0.727	0.903							
CS	0.585	0.646	0.552	0.825						
FM	0.768	0.443	0.418	0.493	0.895					
PBC	0.491	0.672	0.634	0.555	0.275	0.805				
PE	0.516	0.687	0.527	0.566	0.432	0.505	0.852			
PEOU	0.466	0.619	0.510	0.472	0.322	0.598	0.527	0.807		
PU	0.506	0.665	0.637	0.492	0.293	0.663	0.536	0.640	0.870	
SN	0.547	0.698	0.697	0.553	0.305	0.589	0.504	0.467	0.553	0.902

Discriminant validity was evaluated using the Fornell–Larcker criterion and HTMT ratios. As shown in Table 4, the square root of the AVE for each construct was greater than its correlations with other constructs, confirming discriminant validity. To address the limitations of the AVE method, the study also examined HTMT ratios. All HTMT values were below the 0.90 threshold, thereby providing additional support for discriminant validity.

4.2. Structural Model and Hypothesis Test

PLS-SEM was utilized to conduct path analysis for testing the hypothesized relationships. To evaluate the hypothesized paths, the study employed the PLS-SEM estimation method. The robustness of the statistical outcomes was ensured through a bootstrapping process comprising 5.000 iterations. The findings are summarized in Table 5. All hypothesized relationships were found to be statistically significant ($p < 0.05$), except for the paths from PE to BI and CS to BI, whose p-values exceeded the 0.05 threshold. Accordingly, hypotheses H3 and H4 are not supported, while H1, H2, H5, H6, H7, and H8 receive empirical support.

Table 5. Path coefficient results and T-value analysis (hypothesis testing)

Hypothesis	**Path**	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-value	**Hypothesis support or reject**
H1	PBC -> BI	0.186	0.186	0.055	3.360	0.001	Supported
H2	SN -> BI	0.315	0.316	0.051	6.204	0.000	Supported
H3	PE -> BI	0.012	0.013	0.047	0.246	0.805	Rejected
H4	CS -> BI	0.044	0.046	0.048	0.912	0.362	Rejected
H5	ATU -> BI	0.346	0.344	0.061	5.675	0.000	Supported
H6	PU -> ATU	0.456	0.456	0.048	9.542	0.000	Supported
H7	PEOU -> ATU	0.327	0.327	0.047	6.904	0.000	Supported
H8	BI -> AB	0.416	0.415	0.033	12.513	0.000	Supported

Figure 2 demonstrates the structural model, highlighting the estimated path coefficients together with their respective p-values for each variable.

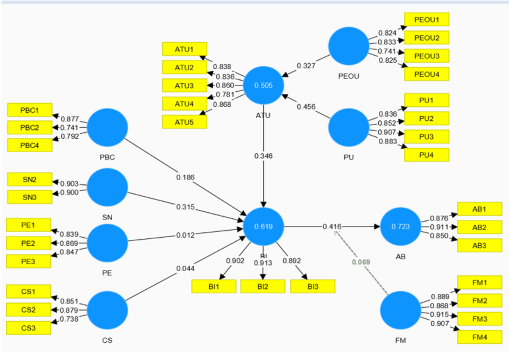

Fig. 2. Structural model showing path coefficient and p-values

Note: PBC: perceived behavioral control; PE: Perceived enjoyment; CS: Computer self-efficacy; PU: Perceived usefulness; PEOU: Perceived ease of use; ATU: Attitudes toward using AI tools; BI: Behvioral intention; AB: Actual behavior; FM: FOMO.

The indirect effect of CS -> BI -> AB and PE -> BI -> AB are not significant, as the p-value is 0.457, which exceeds 0.05. In contrast, the remaining indirect relationships demonstrated statistical significance, as their p-values were all below 0.05.

Table 6. Mediating role of behavioral intention

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATU -> BI -> AB	0.144	0.143	0.028	5.058	0.000
CS -> BI -> AB	0.018	0.019	0.020	0.910	0.363
PBC -> BI -> AB	0.077	0.077	0.024	3.225	0.001
PE -> BI -> AB	0.005	0.005	0.020	0.247	0.805
ATU -> BI -> AB	0.144	0.143	0.028	5.058	0.000
ATU -> BI -> AB	0.144	0.143	0.028	5.058	0.000
SN -> BI -> AB	0.131	0.131	0.024	5.452	0.000

The moderating role of FOMO (FM) in the relationship between behavioral intention (BI) and actual behavior (AB) was found to be statistically significant ($p = 0.027$), which is below the 0.05 threshold. This result supports hypothesis H9, confirming that FOMO moderates the effect of BI on AB. The positive interaction coefficient ($\beta = 0.069$) suggests that higher levels of FOMO strengthen the impact of behavioral intention on the actual use of AI-powered tools.

Table 7. Moderating role of FOMO

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FM x BI -> AB	0.069	0.071	0.031	2.210	0.027

5. DISCUSSION AND RECOMMENDATIONS

5.1. Discussion

The results provide valuable perspective on the factors influencing learners' intention to use and actual engagement with AI-enabled educational technologies in academic contexts. Consistent with expectations, perceived behavioral control (PBC), subjective norm (SN), and attitude toward use (ATU) showed a significant positive effect on behavioral intention (BI). These results suggest that learners show a stronger tendency to adopt AI tools when they believe they have sufficient control over their use, perceive social encouragement from peers or instructors, and hold favorable attitudes toward the technology.

While most hypothesized relationships were supported, two paths were not statistically significant: the influence of perceived enjoyment (PE) on BI ($p = 0.805$) and the role of computer self-efficacy (CS) in predicting BI ($p = 0.362$), leading to the rejection of H3 and H4. In contrast, strong support was found for H1, H2, and H5, reinforcing the importance of control beliefs, social influence, and positive attitudes in determining learners' intention to employ AI-supported educational applications.

Regarding perceived enjoyment, while students in more developed contexts are often exposed to digital ecosystems from early education levels and tend to consider self-exploration of technology as part of their personal learning competencies, Vietnamese students may approach AI tools more cautiously and with a focus on specific goals, such as assisting with assignments, reviewing lessons, or improving academic efficiency. Furthermore, exam pressure and expectations from family and society, typical in Vietnam's highly competitive educational culture may lead students to prioritize AI tool usage for practical and outcome-driven reasons, rather than for enjoyment or technological curiosity. This may explain why perceived enjoyment had an insignificant impact in the current study's model among Vietnamese students, in contrast to previous research findings (Roslan et al., 2021).

Furthermore, the non-significant link between self-efficacy (CS) and behavioral intention (BI) suggests that students' confidence in their ability to use technology does not exhibit stronger intentions to utilize AI-driven applications. This finding contrasts with the results reported by Hayashi et al. (2004), who reported a positive linkage between self-efficacy and technology use. It is possible that in the context of increasingly familiar digital environments, baseline self-efficacy is high across the sample, thereby reducing its predictive power. Together, these findings contribute to the accumulating evidence base suggesting that context matters when evaluating the relevance of motivational constructs in technology acceptance.

Interestingly, the significant moderating role of FOMO between behavioral intention and actual adoption underscores the psychological influence of the fear of missing out in shaping students' technology adoption. Students experiencing higher levels of FOMO are more likely to act promptly on their intentions to adopt AI tools, driven by a stronger desire to stay informed and avoid being left behind. This result aligns with previous findings (Griffiths & Kuss, 2017; Gartner et al., 2022) indicating that FOMO can intensify behavioral responses, particularly in digitally mediated learning environments. It also reflects a common psychological trait among students in today's academic settings, where competitive pressures and the need to keep pace with technological advancements are increasingly prominent. Thus, FOMO serves as a meaningful psychological catalyst in transforming intention into actual behavior within the educational use of AI tools.

5.2. Recommendations

Based on the findings, several practical implications emerge, particularly for stakeholders in the Vietnamese higher education context. First, educators and universities should focus on enhancing students' perceived behavioral control by integrating AI training into curricula and ensuring access to supportive resources. Promoting positive subjective norms, for instance, through instructor endorsement and peer advocacy can further encourage adoption. Since perceived enjoyment did not significantly influence intention, efforts should emphasize the utility and academic relevance of AI tools over entertainment.

For AI developers, designing tools with intuitive interfaces and features aligned with local academic demands, such as test preparation, translation support, and time-saving functions can increase perceived usefulness and engagement. Finally, students themselves should be encouraged to move beyond a purely instrumental view of AI and explore its potential for deeper learning, skill development, and long-term academic growth. In a competitive and exam-oriented Vietnamese context, fostering a mindset of proactive digital literacy is essential for maximizing AI's benefits in education.

6. CONCLUSION

This research examined the major influences on Vietnamese university students' willingness and usage behaviors in adopting AI-based educational technologies, drawing upon the Technology acceptance model (TAM), the Theory of planned behavior (TPB), and the psychological construct of FOMO. The findings confirmed that

perceived control, social influence, and user attitude significantly shape students' behavioral intentions, while perceived enjoyment and computer self-efficacy showed no significant effect in this academic context.
Moreover, the study underscores the pivotal moderating function of FOMO in the relationship between intention and behavior, emphasizing the growing influence of psychological factors in technology adoption among students. These insights contribute to a deeper understanding of how Vietnamese students approach emerging educational technologies not solely for enjoyment, but with a pragmatic focus on academic effectiveness.

In sum, the research offers valuable implications for educators, universities, and AI developers, suggesting that enhancing control, social influence, and perceived usefulness are more effective strategies than focusing on hedonic motivation. Future studies may benefit from expanding the sample across multiple institutions or incorporating qualitative insights to further contextualize student perceptions.

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