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Determinants of ChatGPT adoption for learning among students in Thailand's private higher education sector: An integrated TAM–UGT approach

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ABSTRACT

Generative AI, particularly ChatGPT, has found its way into how students search for information, write, and revise their academic work. This research raised the question of what shapes students' intention to use ChatGPT, based on two technology adoption theories: the Technology Acceptance Model and Uses and Gratifications Theory. Five factors, perceived value, attitude toward use, academic content creation, information seeking, and novelty, were assessed to predict behavioral intention. A sample of 500 undergraduate and graduate students at private universities in Thailand was surveyed. Content validity was assessed using the Item-Objective Congruence index, and the instrument was piloted with 50 respondents (Cronbach's $\alpha > 0.80$). Confirmatory factor analysis confirmed measurement quality, and structural equation modeling tested the hypotheses. Four of the five factors showed significant relationships: academic content creation had the strongest effect ($\beta = 0.44$, $p < 0.001$), followed by information seeking ($\beta = 0.38$, $p < 0.001$), perceived value ($\beta = 0.20$, $p < 0.001$), and novelty ($\beta = 0.12$, $p < 0.05$); attitude toward use did not show a significant relationship ($\beta = 0.01$, $p > 0.05$). In practical terms, students could achieve their academic goals through the use of ChatGPT, which highlighted their willingness to use it more than their feelings about its use. The study debates that higher education needed to provide guidance for the integration of learning and using Generative AI in a response of information literacy and efficient tools used rather than promoting the attitude in accordance with the motivation based on gratification model.

Contribution/Originality: This study contributes to the existing literature as one of the first to combine the Technology Acceptance Model with Uses and Gratifications Theory to discuss ChatGPT usage in Thailand's private universities, showing that gratification-based motivation is substantially higher than attitudes and reframing the adoption of generative AI in academic environments.

1. INTRODUCTION

1.1. The Adoption of Generative AI in Higher Education

Generative artificial intelligence (AI) has moved from a trial tool to an everyday feature of academic life, and few tools illustrate this shift more clearly than ChatGPT. Since the tool was released publicly, students have widely used it for searching, writing, revising, grammar checking, or even generating new ideas for their academic projects, alongside being a useful tool for academic personnel, including teachers, researchers, and tutors (Rahman, Sabbir, Zhang, Moral, & Hossain, 2023; Shahzad, Xu, & Javed, 2024). The rapid adoption has signaled to the higher education sector concerns about ethical use, digital literacy, readiness for application, and the provision of guidance for

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responsible use (Al-Abdullatif & Alsubaie, 2024; Le, Do, Tran, Dang, & Nguyen, 2026). The factors and reasons why students intend to use Generative AI tools have been widely discussed and questioned among educators and policymakers.

The Ministry of Higher Education has developed a roadmap for the nation's digital transformation, and questions have been raised about the motives behind students' use of ChatGPT to assist them with writing, content creation, and examination preparation (Shaengchart et al., 2023). The adoption of ChatGPT is underlined by psychological and motivational drivers that dictate students' perceptions of its value, benefits, and novelty, and examining these factors is vital for the higher education sector to encourage AI literacy and raise the country's academic standards (Aguilos & Fuchs, 2024). Private universities are competing to design student experiences and integrate innovation with academic content. However, limited empirical research has examined the dynamics of these tools, identifying a research gap in exploring the motivational predictors of ChatGPT usage.

Previous literature has spotlighted two reputable models to indicate adoption behavior. The Technology Acceptance Model (TAM) laid out perceived usefulness, perceived ease of use, and attitudes (Davis, 1989), while Uses and Gratifications Theory (UGT) explicates the channels and uses of technology through which users actively seek information, novelty, and creativity (Le et al., 2026). These two theories have been applied to the adoption of ChatGPT separately: TAM has been used to study the effects of value understanding and perception, and UGT has been used to study the relationship between information seeking, academic content creation, and novelty and students' intentions to use ChatGPT (Rahman et al., 2023; Yum & Kim, 2024).

According to prior studies, there are three unsolved problems. First, TAM and UGT are separated, which makes the motives, such as perceived value, attitude, and gratification attributes, unclear, including information seeking, academic content creation, and novelty, which may influence behavioral intention. Second, there are varying findings regarding attitude, with some research finding a strong effect and others not, suggesting that attitude may be overshadowed by more instrumental motives in this context. Third, previous studies have focused on Western and East Asian environments and public institutions; these dimensions have not been collectively investigated in Thailand's private higher education sector, where usage behavior may differ. Therefore, this research seeks to bridge these gaps through the integration of frameworks, explaining how the technology is adopted.

The research pointed out these gaps by unifying TAM and UGT to examine the impacts of perceived value, attitude toward use, academic content creation, information seeking, and novelty on students' behavioral intention to use ChatGPT for academic goals. The survey was distributed to 500 students at private universities in Thailand. The data were analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM), which identify motives and drivers that have a significant effect on the adoption of ChatGPT. In addition, three contributions were drawn. First, the integration of TAM and UGT for generative AI adoption offers strong evidence in the context of psychological attributes and beneficial motives, which illuminate technology use among private higher education institutions in Thailand, an area that has been underexamined.

Accordingly, the study provides two questions of the research.

RQ1: To what extent do perceived value, attitude toward use, academic content creation, information seeking, and novelty influence students' behavioral intention to use ChatGPT for learning?

RQ2: Which of these cognitive and gratification-based factors most strongly drives ChatGPT adoption within Thailand's private higher education sector?

2. LITERATURE REVIEW

The theoretical review that follows builds the case for five predictors of students' intention to use ChatGPT, which are perceived value, attitude toward use, academic content creation, information seeking, and novelty, and locates each within the two theories that frame this study. Reading TAM and UGT together, it treats adoption as a matter of both how students judge the tool and what they want from it.

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2.1. Technology Acceptance Model and Uses and Gratifications Theory (UGT)

TAM has endured as a reference point for adoption research because it explains a great deal with very little: Davis (1989) proposed that two beliefs, perceived usefulness and perceived ease of use, govern people's intentions regarding technology use. In the context of ChatGPT applications, the research model examines the motivational factors underlying students' adoption, namely the tool's effectiveness and ease of use (Rahman et al., 2023), and recent research has explained that beliefs about using AI lead to higher acceptance through trust and familiarity (Shahzad et al., 2024). Because ChatGPT provides learning solutions for information searching, refining reports, and generating new ideas, students see the benefits of achieving their academic goals (Le et al., 2026). Nevertheless, the model has underexamined why users explore the tools at an early stage.

While TAM identifies users' responses, UGT expands on why users use technological tools. Katz, Blumler, and Gurevitch (1973) argued that active adopters seek tools that meet their specific needs, including information seeking, creativity, and social connection. Through the lens of AI applications, the pursuit of academic and intellectual motives demonstrates usefulness. Le et al. (2026) presented the relationship between knowledge acquisition, curiosity, idea generation, and engagement, whereas Al-Abdullatif and Alsubaie (2024) linked the perceived enjoyment and novelty of the tools to continuous use. Additionally, Jo and Park (2024) explained that informational and hedonic motives serve as drivers. Following these studies, the two theories offer different aspects of the same identified behavior of use, which TAM explains through reasoned appraisal and UGT through motivated search.

This research unified these two theories to dictate technology use behavior rather than selecting one of them. Among several studies, Le et al. (2026) integrated TAM and UGT and found that TAM presents cognitive constructs, whereas UGT assumes gratifications are moderators of ChatGPT use among Vietnamese students, suggesting that neither alone gives a clear picture of behavior. The current frameworks, thus, work in pairs to express cognitive appraisal (Perceived value, attitude) with the aspects of gratifications (Academic content creation, information seeking, novelty).

2.2. Perceived Value

Perceived value refers to the time and effort that students sacrifice to use the technology. Zeithaml (1988) identified value as a vital factor that drives usage intention in the service sector. In the context of ChatGPT use, Al-Abdullatif and Alsubaie (2024) identified value as one of the strong motivators of usage intention, and Baidoo-Anu and Ansah (2023) dictated that the productivity and self-directed learning are perceived by students' decision to use. In the realm of AI tools, the accuracy of the ChatGPT is perceived as trade off value among users (Rudolph, Tan, & Tan, 2023) which makes value a critical factor influencing intentional behavior.

H_1: Perceived value has a significant impact on university students' intention to use ChatGPT.

2.3. Attitude Toward Use

Attitude toward use reflects how students feel about the use of ChatGPT for academic work, and TAM provides a model of technology use (Davis, 1989). Prior literature supports the relationship between attitude and intention to use. Rahman et al. (2023) found that trust and usefulness established positive attitudes toward the intention to use. In light of this, users' feelings are often mixed due to the complexity of Generative AI; thus, enthusiasm runs alongside worries about plagiarism, over-reliance, and integrity (Aguilos & Fuchs, 2024; Mahama, Baidoo-Anu, Eshun, Ayimbire, & Eggley, 2023). This study tests whether a positive attitude influences intention when explicit benefits are in play.

H_2: Attitude toward use has a significant impact on university students' intention to use ChatGPT.

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2.4. Academic Content Creation

Academic content creation refers to students using ChatGPT to draft, revise, and refine essays, reports, and research ideas (Le et al., 2026). The attractive elements are that the tool practically assists with the quality of work, reduces time, and eases heavy workloads (Chan, Wong, Ngai, Fok, & Wang, 2023) and Meluwu and Neman (2025) indicated that students who received good academic results and learning performance would be inclined to use it. Academic content creation has been widely discussed in the context of integrity of use, including Mahama et al. (2023), who flagged that using AI to write can decrease students' originality of work and creative skills, thereby raising clear integrity concerns. Content creation influences adoption while unsettling pedagogy and raises questions about the intention to use it in the Thai environment.

H_3: Academic content creation has a significant impact on university students' intention to use ChatGPT.

2.5. Information Seeking

Information seeking involves the use of ChatGPT to search for, condense, and cross-check information (Yang, Lee, Wu, Zhang, & Pan, 2023). In the UGT model, searching for information is a major gratification. Le et al. (2026) identify information seeking as a prime predictor of the intention to use ChatGPT in self-directed learning, and Jo and Park (2024) suggest that AI tools support knowledge acquisition, but debates about accuracy and sources persist due to the variability of their data pools. In most cases, Thai students turn to ChatGPT to clarify concepts and gain a clearer understanding of information (Shaengchart et al., 2023). Accuracy is still debated, however. Rudolph et al. (2023) posit that ChatGPT can provide answers fluently but incorrectly, which might either discourage its use or, just as conceivably, encourage it as a validation tool trusted by students.

H_4: Information seeking has a significant impact on university students' intention to use ChatGPT.

2.6. Novelty

Novelty can illuminate the intrinsic motives associated with encountering something new, which attract students to use new tools by encouraging them to believe that they can solve problems (Le et al., 2026). Alzyoud et al. (2024) found that perceived novelty influenced both attitudes and intentions toward using AI tools, embedding it as a gratification of intrinsic value rather than short-term excitement. Novelty is a significant factor in the intention to use. Shahzad et al. (2024) noted that early excitement usually fades unless clear benefits are foreseen; therefore, novelty may attract adoption in the long term.

H_5: Novelty has a significant impact on university students' intention to use ChatGPT.

2.7. Intention to Use ChatGPT

Behavioral intention, the outcome variable here, captures a student's readiness to utilize ChatGPT for learning and, on the logic above, follows from both appraisal and motivation (Aguilos & Fuchs, 2024). Prior studies show that usefulness, trust, and value raise intention (Al-Abdullatif & Alsubaie, 2024; Rahman et al., 2023) and that gratifications such as content creation, information seeking, and novelty sustain it (Le et al., 2026). What has rarely been tested is how these forces behave together, whether TAM's attitudinal path still carries weight once gratifications enter the same model.

2.8. Conceptual Framework

Unifying the two theoretical models, the theories present the intention to use ChatGPT as the output of two cognitive appraisals, including perceived value and attitude, and three gratifications, including academic content creation, information seeking, and novelty. The evidence from previous literature confirms the relationship among them (Al-Abdullatif & Alsubaie, 2024; Rahman et al., 2023), while intrinsic gratifications prolong engagement with use (Le et al., 2026). Figure 1 illustrates the five hypotheses.

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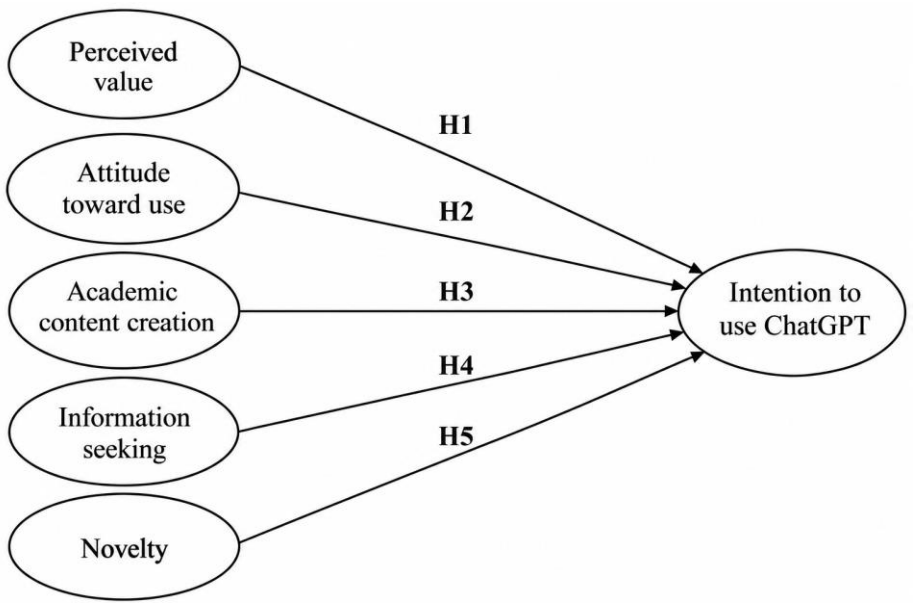


Figure 1. Conceptual framework.

3. RESEARCH METHODOLOGY

3.1. Population and Samples

Undergraduate and graduate students from the ten largest private universities in Thailand by student enrollment are used as the study population. The data set uses October 2025 enrollment data, targeting students who have experience using ChatGPT for academic work. Within this framework, the study targets only students who have worked with the tool and could understand the motives behind its utilization. Kline (2015) states that samples over 200 are a proper size for structural equation modeling; thus, the study determines that 500 students is an appropriate sample size. The ten universities were validated using the enrollment numbers published by the Ministry of Higher Education Science Research and Innovation (2024) and had to meet three qualifications. First, the ten largest private universities are ranked. Second, total enrollment in Semester 1 of 2025 is accepted. Third, digital or AI-assisted learning tools are currently in use. Focusing on the largest private institutions provides an efficient study group for using ChatGPT and shows that investment and infrastructure are most developed.

3.2. Research Instrument

The structured questionnaire was adapted from prior validated scales, with each item rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Every construct comprised several items that convey the questionnaire in the context of the study. Perceived value (PV) has six items exemplified by "ChatGPT provides responses and suggestions tailored to my academic needs and preferences" (Yum & Kim, 2024); attitude toward use (ATU) has four items exemplified by "I want to use ChatGPT for my academic purpose" (Rahman et al., 2023); academic content creation (ACT) has six items exemplified by "I utilize ChatGPT to work on my assignments" (Le et al., 2026); information seeking (IS) has seven items exemplified by "I search for information I need by using ChatGPT" (Le et al., 2026); novelty (NV) has six items exemplified by "ChatGPT is a new tool to use" (Le et al., 2026); and intention to use (ITU) has three items exemplified by "I am willing to use ChatGPT for my academic learning" (Kordzadeh, 2019).

There is a two-step validation process. According to Rovinelli and Hambleton (1977), content validity was first validated by three experts, including two specialists in technology adoption and a lecturer experienced in AI-integrated teaching. The three experts rated each item for relevance, clarity, and fit with its construct. The validated items were retained if they scored at or above .60 on the index of item-objective congruence. Fifty students were used

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as a pilot group to check reliability, with every construct clearing the .70 threshold (Nunnally & Bernstein, 1994). Cronbach's alpha results were as follows: perceived value $\alpha = 0.88$, attitude toward use $\alpha = 0.84$, academic content creation $\alpha = 0.90$, information seeking $\alpha = 0.87$, novelty $\alpha = 0.85$, and intention to use $\alpha = 0.83$. Internal consistency met the criteria.

Because the respondents were Thai, the English instrument was translated into Thai using back-translation to ensure accurate meaning (Maneesriwongul & Dixon, 2004). In this method, two bilingual experts translated it independently, another pair translated it back, and the team reconciled any gaps by consensus so that the wording and meaning remained clear and accurate.

3.3. Collection of Data

The data collection period ran from November 2025 to February 2026. The sampling techniques used were judgmental, quota, convenience, and snowball sampling (Kline, 2015). Judgmental sampling identified the target group of students who were within the ten largest private universities and used ChatGPT as a tool to assist with their coursework. Quota sampling generalized the proportional sample size using the Ministry's Semester 1 2025 enrollment counts (as of 1 October 2025). Convenience sampling recruited active volunteers, and snowball sampling referred peers who also had experience using ChatGPT. The procedure yielded 500 valid responses gathered online and in person, each preceded by a statement of the study's aims, its anonymity, and the voluntary nature of responding to the questionnaire. Before participating, all respondents received information describing the study's aims, procedures, anonymity, and their right to withdraw at any time without penalty. For the online questionnaire, informed consent was obtained electronically: respondents were required to read the consent statement and tick a box indicating their agreement to participate before accessing the survey items, and those who did not consent could not proceed. For the in-person questionnaire, respondents read the same information and signed a written consent form before completing the survey. This procedure was approved by the AU Institutional Review Board of Assumption University (Approval No. 159/2025).

In this study, non-probability techniques were explicitly considered to identify potential sources of sampling bias. Convenience and snowball sampling may have overrepresented students who are already active ChatGPT users or who are closely connected to the peer group, which may inflate reported adoption and limit generalizability to non-users. Quota sampling was applied to counterbalance this by ensuring proportional representation across the ten largest private universities, as well as across levels of adoption and ChatGPT experience. Since the research examined the propensity for continued behavioral intention rather than awareness, bias may exist. The limited sample size conveys boundaries and limitations, as the results may not be applicable to smaller colleges, opening a gap for further discussion or future studies.

3.4. Data Analysis

A structural equation modeling (SEM) approach was adopted to test hypotheses. In this model, the measurement model and the structural model were examined separately (Hair, Black, Babin, & Anderson, 2010; Kline, 2015). SEM was selected in preference to partial least squares SEM (PLS-SEM) because the study used a confirmatory rather than an exploratory approach. SEM is a useful tool for examining the constructs and their relationships based on TAM and UGT. Moreover, the large sample ($n = 500$), with multi-item, normally distributed indicators, underpinned SEM's good model-fit testing. While some previous ChatGPT-adoption research has applied regression or PLS-SEM techniques that focus on predictors, SEM provides model-fit diagnostics that permit the evaluation of the study's two key models. Therefore, TAM and UGT were structured and evaluated.

Following the SEM, this study assessed confirmatory factor analysis to test whether each indicator loaded on its intended latent construct and whether the measurement model fit. Model fit was verified according to the criteria proposed by Hair et al. (2010).

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Apart from the measurement model, the structural model was used to test hypothesized paths, demonstrating the relationships between perceived value, attitude toward use, academic content creation, information seeking, novelty, and intention. Standardized path coefficients indicated the size and significance of each relationship, providing the significance level for each path.

4. RESULTS

As shown in Table 1, the demographic data show that most respondents were undergraduates (82%), concentrated in the 21–23 age band (48%), and most often enrolled in Business and Management programs (29%). The largest sample group had experience with ChatGPT for 7–12 months (35%).

Table 1. Demographic results.

Demographic and general data (N=500)	Frequency	Percentage
Gender		
Male	230	46.00
Female	265	53.00
Prefer not to say	5	1.00
Level of study		
Undergraduate	410	82.00
Graduate	90	18.00
Age group		
18–20 years old	155	31.00
21–23 years old	240	48.00
24–26 years old	70	14.00
27 years old and above	35	7.00
Field of study		
Business / Management / Economics	145	29.00
Engineering / Technology / Computer Science	120	24.00
Humanities / Social Sciences / Education	105	21.00
Arts / Design / Communication	70	14.00
Science / Health / Other	60	12.00
Experience using ChatGPT		
Less than three months	80	16.00
Three to six months	160	32.00
Seven to twelve months	175	35.00
Over one year	85	17.00
Total	500	100.00

In Table 2, the measurement model showed that Cronbach's alpha ranged from 0.84 to 0.88, exceeding the 0.70 criterion for internal consistency (Hair et al., 2010). Standardized loadings ranged from 0.61 to 0.87, verifying convergent validity (Kline, 2015). Composite reliability ranged from 0.84 to 0.88, which was above the 0.70 cutoff. Finally, average variance extracted ranged from 0.44 to 0.72, meeting the 0.40 standard (Fornell & Larcker, 1981). The results confirm the reliability and validity of the data for testing students' intention to use.

Table 2. The results of confirmatory factor analysis, composite reliability (CR), and average variance extracted (AVE).

Variables	Source of questionnaire	No. of items	Cronbach's α (n=500)	Factor loading	CR	AVE
Perceived value (PV)	Yum and Kim (2024)	6	0.86	0.68–0.73	0.86	0.50
Attitude toward use (ATU)	Rahman et al. (2023)	4	0.84	0.69–0.81	0.84	0.56
Academic content creation (ACT)	Le et al. (2026)	6	0.84	0.63–0.73	0.84	0.47
Information seeking (IS)	Le et al. (2026)	7	0.84	0.61–0.71	0.85	0.44
Novelty (NV)	Le et al. (2026)	6	0.88	0.64–0.82	0.88	0.55
Intention to use ChatGPT (ITU)	Kordzadeh (2019)	3	0.88	0.83–0.87	0.88	0.72

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Discriminant validity was assessed using the Fornell–Larcker criterion, which compares the square root of each construct's average variance extracted with its correlations with the other constructs. In Table 3, the diagonal square roots (in bold) exceed all off-diagonal correlations, indicating that each construct- perceived value, attitude toward use, academic content creation, information seeking, novelty, and intention- is empirically distinct from the others (Fornell & Larcker, 1981).

Table 3. Discriminant validity.

Variables	NV	PV	ATU	ACT	IS	ITU
NV	0.74					
PV	0.22	0.71				
ATU	0.18	0.49	0.75			
ACT	0.25	0.52	0.57	0.68		
IS	0.24	0.63	0.65	0.66	0.66	
ITU	0.28	0.54	0.46	0.66	0.66	0.85

Note: The diagonal values (in bold) represent the square roots of the AVE for each construct. NV = Novelty, PV = Perceived value, ATU = Attitude toward use, ACT = Academic content creation, IS = Information seeking, ITU = Intention to use ChatGPT.

Every measurement-model index cleared its threshold, signaling a strong fit to the data Table 4; (Hair et al., 2010; Kline, 2015). The structural model, after modification, also fit acceptably ($\chi^2/df = 2.74$, GFI = 0.85, CFI = 0.90, RMSEA = 0.06), so both models were sound enough to carry the hypothesis tests.

Table 4. Goodness of fit for measurement and structural models.

Index	Fit values	Measurement model (No modification)	Structural model (Before modification)	Structural model (After modification)
CMIN/DF	< 3.00 (Hair et al., 2010)	705.59/449 = 1.57	1333.03/459 = 2.90	1233.53/451 = 2.74
GFI	≥ 0.85 (Kline, 2015)	0.92	0.84	0.85
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.91	0.82	0.83
NFI	≥ 0.80 (Wu & Wang, 2006)	0.91	0.83	0.84
CFI	≥ 0.80 (Bentler, 1990)	0.97	0.88	0.90
TLI	≥ 0.80 (Sharma, Mukherjee, Kumar, & Dillon, 2005)	0.96	0.87	0.88
RMSEA	< 0.08 (Pedroso et al., 2016)	0.03	0.06	0.06
Model summary		Consistent with empirical data	Inconsistent with empirical data	Consistent with empirical data

Note: CMIN/DF = chi-square/Degrees of freedom; GFI = Goodness-of-fit index; AGFI = Adjusted goodness-of-fit index; NFI = Normalized fit index; CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation.

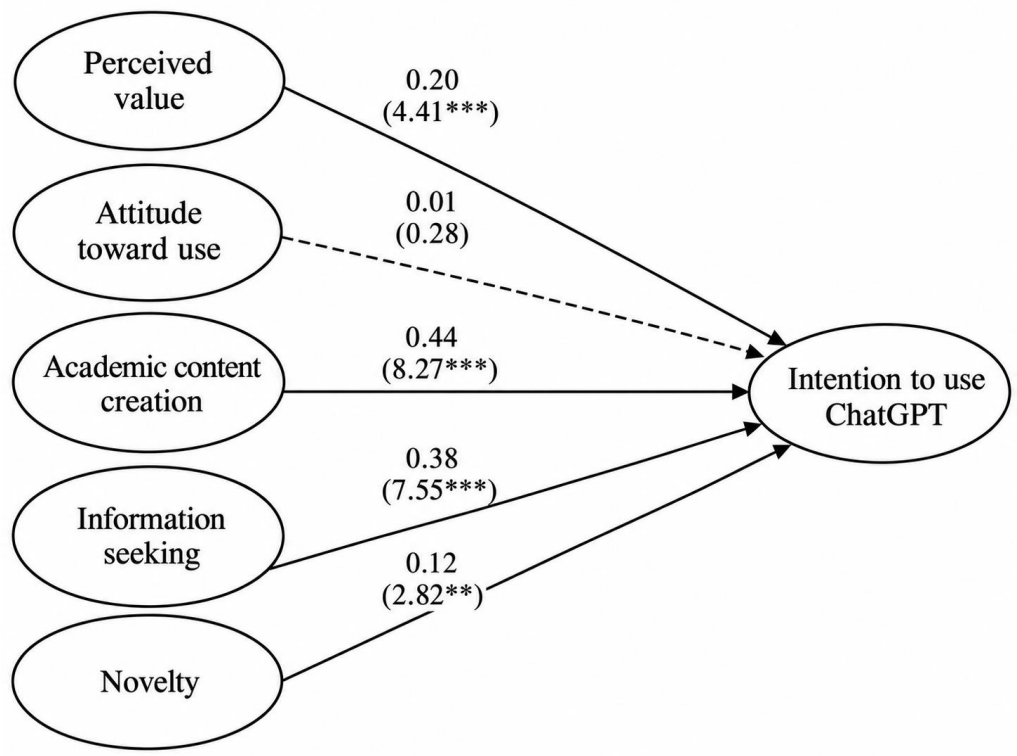
Table 5 and Figure 2 report the key structural results. The output presents standardized coefficients (β), standard errors, and t-values, with significance values at $p < 0.05$ (Hair et al., 2010). Estimating the five paths together allowed their relative influence on intention to be compared directly rather than one at a time.

Table 5. Testing result of research hypotheses.

Hypotheses	Paths	Standardized path coefficients (β)	S.E.	T-value	Test result
H1	PV → ITU	0.20	0.05	4.41***	Supported
H2	ATU → ITU	0.01	0.04	0.28	Not supported
H3	ACT → ITU	0.44	0.06	8.27***	Supported
H4	IS → ITU	0.38	0.06	7.55***	Supported
H5	NV → ITU	0.12	0.04	2.82**	Supported

Note: **p < 0.05; ***p < 0.001. PV = Perceived value, ATU = Attitude toward use, ACT = Academic content creation, IS = Information seeking, NV = Novelty, ITU = Intention to use ChatGPT.

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Note: Dashed lines show not significant whereas solid lines show significant. **p < 0.05; ***p < 0.001.

Figure 2. The results of structural model.

The analysis examined five hypotheses regarding the impact of various factors on students' intention to use ChatGPT in higher education, as shown in Table 5 and Figure 2.

H_1: Perceived value had a significant, positive effect on intention ($\beta = 0.20$, $p < 0.001$), supporting the hypothesis.

H_2: Attitude toward use showed no significant link to intention ($\beta = 0.01$, $p > 0.05$); the hypothesis was not supported.

H_3: Academic content creation had a strong significant impact on intention ($\beta = 0.44$, $p < 0.001$), giving the hypothesis firm support.

H_4: Information seeking likewise raised intention ($\beta = 0.38$, $p < 0.001$), confirming the hypothesis.

H_5: Novelty had a smaller but significant positive effect ($\beta = 0.12$, $p < 0.05$), supporting the hypothesis.

5. RESULTS AND DISCUSSION

The research investigated the primary determinants affecting university students' intention to use ChatGPT for academic purposes, grounded in two theories: the technology acceptance model (TAM) and uses and gratifications theory (UGT). The findings offer empirical insights into how cognitive, motivational, and experiential factors drive ChatGPT adoption in higher education. Overall, the results revealed that perceived value, academic content creation, information seeking, and novelty significantly influenced intention to use ChatGPT, while attitude toward use did not.

Perceived value showed a significant positive effect on students' intention to use ChatGPT ($\beta = 0.20$, $p < 0.001$), consistent with previous studies and TAM theory, which link usefulness and satisfaction in technology adoption (Yum & Kim, 2024; Zeithaml, 1988). The findings can be implied practically that perceived value is concrete in recognizing the benefits of use among students towards ChatGPT. The beliefs are that the AI tools assist to improving efficiency and study performance which resides in the studies, while favorably attitude alone is not enough. Additionally, universities should identify tasks for which AI tools can efficiently support drafting, idea generation, and time savings, thereby encouraging learners to adopt these tools.

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Academic content creation had the strongest effect on students' intention to use ChatGPT ($\beta = 0.44$, $p < 0.001$), aligning with prior literature showing that ChatGPT enhances writing, creativity, and the refinement of academic work (Al-Abdullatif & Alsubaie, 2024; Le et al., 2026). In practical terms, the findings indicate that content creation is a key factor driving behavioral intention, encouraging students to use ChatGPT for learning and task completion. Because AI tools are widely available, institutions should guide their responsible use, with particular attention to academic integrity and authorship. Similarly, information seeking had a significant effect on intention to use ($\beta = 0.38$, $p < 0.001$), suggesting that ChatGPT provides convenient, on-demand access to a large body of information that can be used comprehensively for self-directed learning (Rahman et al., 2023; Shaengchart et al., 2023). The effect size supports the argument that AI-generated information is in high demand for academic purposes.

Furthermore, novelty had a significant effect on intention ($\beta = 0.12$, $p < 0.05$), affirming UGT's assumptions regarding curiosity and intrinsic motivation, which predict users' engagement with new technologies (Alzyoud et al., 2024; Le et al., 2026). Novelty carries greater weight than informative constructs. Although novelty may occur during early use, it showed more significant coefficients than content creation and information seeking, suggesting that adoption can be sustained by functional benefits rather than excitement. This finding reflects that novelty may fade unless the perception of value persists (Shahzad et al., 2024). On the other hand, attitude toward use ($\beta = 0.01$, $p > 0.05$) did not significantly affect intention, indicating that although students may hold positive views about use, this alone is insufficient to predict behavior without perceived value or benefits (Rahman et al., 2023). These results echo prior literature on attitudes toward ChatGPT use, which suggests that once value- and gratification-based motives are accounted for, general attitude adds little explanatory power (Sabbir, Akter, Khan, & Das, 2020).

In summary, these findings highlight that both instrumental and experiential gratifications, including usefulness, creativity, and curiosity, are significant drivers of students' behavioral intentions to adopt ChatGPT. The results refine the theoretical foundations of TAM within a UGT-based framework and enhance understanding of AI integration in educational contexts. Specifically, the integration of TAM and UGT provides an integrated framework for this study. It shows that gratification-based motives outperform TAM's attitudinal constructs in explaining the adoption of generative AI within Thailand's private higher education sector.

6. CONCLUSION

This study examined the significant drivers of university students' intentions to use ChatGPT for academic purposes in the private higher education sector in Thailand, emphasizing perceived value, attitude toward use, academic content creation, information seeking, and novelty. The findings revealed that perceived value, academic content creation, information seeking, and novelty had significant effects on students' behavioral intentions. In contrast, attitude toward use did not have a significant effect. These findings indicate that students' adoption of ChatGPT is shaped by factors beyond its functional benefits and the intrinsic motivations associated with attitude, reflecting broader considerations. The study addressed previously identified gaps by examining the integration of TAM and UGT. It clarifies the limited role of attitudes toward the use of AI tools and provides evidence from an underexamined institutional context.

6.1. Theoretical Implications

The findings provide a clearer understanding of the technology acceptance model (TAM) and uses and gratifications theory (UGT) by demonstrating how perceived value and information sourcing interact with intrinsic motivations, such as inquisitiveness and novelty, to predict AI adoption in institutions. The study contributes by confirming that an integrated TAM-UGT model, in which gratification-based motives are emphasized, explains ChatGPT adoption more strongly than the attitudinal pathway. It also demonstrates how the two frameworks can be integrated in generative AI contexts.

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6.2. Practical Implications

In practice, educators and policymakers should recognize the importance of promoting ChatGPT as both a learning enhancement tool and a creative learning partner. ChatGPT can serve as an important tool for encouraging critical thinking, responsible use, and academic integrity. Because academic content creation is a significant predictor of the intention to use ChatGPT, guidance on responsible authorship is needed to encourage students' active engagement. In addition, cultivating awareness, providing training, and improving digital literacy can strengthen students' ability to use AI ethically and effectively.

6.3. Limitations

Several limitations should be acknowledged in this research. First, data were collected solely from students enrolled in private universities in Thailand, which may limit the generalizability of the findings to public institutions and other educational contexts. Second, the self-reported questionnaire used in this study may be subject to response bias, particularly when examining behavioral intentions toward evolving technologies. Third, the cross-sectional design limits the ability to infer causality or capture changes in students' perceptions over time as AI technologies continue to evolve. Lastly, the study focused on selected psychological and motivational factors; future research could examine additional factors.

6.4. Future Research

Future studies could expand this examination to encompass diverse educational systems and cultural contexts, including public institutions, or employ longitudinal and mixed-method designs to explore how students' perceptions and behaviors evolve as generative AI becomes a common tool and learning partner in higher education. Extending the constructs to include digital competence, ethical concerns, and institutional support could also provide a more comprehensive interpretation of ChatGPT adoption in higher education.

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