Trust, Usefulness, and Satisfaction in ChatGPT Adoption: An ELM–TAM Study among University Students

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***Abstract*—This study integrates the Elaboration Likelihood Model (ELM) and the Technology Acceptance Model (TAM) to examine how trust mediates the cognitive and emotional mechanisms underlying students' continued use of generative Artificial Intelligence (AI) chatbots—specifically, ChatGPT. A bibliometric analysis of 21 studies from the Web of Science database (2010–2025) reveals limited integration of ELM and TAM in educational AI contexts, highlighting a theoretical gap. To address this, we developed a dual-path model combining cognitive constructs (e.g., perceived usefulness, information quality) and affective cues (e.g., fairness, accountability, transparency), with trust serving as a mediating variable. A survey of 359 Vietnamese university students was analyzed using Structural Equation Modeling (SEM) and Multi-Group Analysis (MGA) to examine how ChatGPT usage duration moderates the persuasive process. Findings indicate that peripheral cues (e.g., fairness, accountability) significantly shape trust across user groups. However, the central route (information quality) on trust is heavily moderated by user experience: while it exerts a strong effect on low-frequency users, its impact is significantly attenuated—to less than half the strength—among high-frequency users. Furthermore, trust strongly predicts both satisfaction and perceived usefulness, with satisfaction emerging as the most powerful determinant of continuance usage intention. The study contributes to theory by validating the integration of ELM and TAM in the context of AI adoption and highlighting the moderating role of usage frequency. Practical implications include promoting AI literacy and designing chatbot interfaces with greater transparency to meet the cognitive expectations of experienced users.**

***Keywords*—ChatGPT adoption, Elaboration Likelihood Model (ELM), Technology Acceptance Model (TAM), trust, higher education**

I. Introduction

The emergence of generative Artificial Intelligence (AI) tools has sparked a significant shift in how individuals collect, organize, and produce knowledge. Among these, ChatGPT—released by OpenAI on Nov. 30, 2022 [1]—has quickly become one of the most widely adopted AI chatbot platforms. Since its release, ChatGPT has gained substantial traction for its ability to support brainstorming, content generation, and language improvement in academic settings [2, 3]. As higher education environments increasingly embrace AI tools, understanding the psychological and technological determinants of their continued use becomes a pressing research concern.

University students are a relevant population for studying AI adoption due to their high digital literacy and exposure to emerging technologies. Numerous recent studies have explored student behavior toward ChatGPT [4–7]. Most of these studies apply established theoretical models such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), or the Theory of Planned Behavior (TPB), and consistently identify Perceived Usefulness (PU) as a key driver of intention to use [8–10]. However, sustained use of ChatGPT remains inconsistent [11, 12], suggesting that existing models may overlook key explanatory variables.

One notable limitation of TAM lies in its emphasis on rational cognitive factors (e.g., usefulness, ease of use) while neglecting emotional and heuristic influences—elements that are highly relevant in AI-human interaction contexts. The Elaboration Likelihood Model (ELM) offers a complementary framework, distinguishing between central (logic-and content-driven) and peripheral (emotion-and cue-driven) routes of persuasion [13]. While the integration of ELM and TAM has indeed been explored in domains such as e-commerce and mobile services [14], its application to generative AI in education presents a fundamentally different context that demands theoretical refinement. In traditional technology adoption, system outputs are typically deterministic and based on curated data. In contrast, generative AI like ChatGPT produces non-deterministic, probabilistic outputs that can vary in quality, accuracy, and even ethical alignment (e.g., "hallucinations," bias) [12, 15]. This inherent uncertainty and opacity of AI systems elevate the user's task from mere functional acceptance to continuous epistemic judgment—assessing not just if the tool works, but if it can be trusted as a source of reliable knowledge.

This study argues that the ELM-TAM integration is not merely a repetition of a known model but a necessary framework to dissect the dual-process reasoning that students employ in this high-stakes, high-uncertainty environment. The ELM provides the crucial lens to understand how students form these judgments—either through effortful scrutiny of Information Quality (IQ) (central route) or through reliance on heuristic ethical cues like fairness and transparency (peripheral route). The TAM, with trust positioned as a pivotal mediator replacing the less salient Perceived Ease of Use (PEOU), then explains how these judgments translate into sustained adoption behavior via Perceived Usefulness (PU) and satisfaction. Therefore, the theoretical necessity of this integration lies in its ability to unpack the "black box" of trust formation in AI, moving beyond the generic finding that "trust mediates" to explain which specific pathways (central vs. peripheral) build this trust and how their influence evolves with user

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experience—a nuance critical for AI but less salient in more predictable technological domains. This combined theoretical and empirical approach responds to calls for more comprehensive models that account for both rational and emotional influences in AI adoption [10].

Building on the growing interest in generative AI tools in education, particularly ChatGPT, this study aims to achieve the following objectives:

1) To systematically review and synthesize existing empirical studies on the integration of ELM and TAM in technology adoption contexts, with a focus on identifying theoretical convergence and research gaps through bibliometric analysis.
2) To develop and empirically validate a comprehensive conceptual model that integrates key constructs from ELM (central and peripheral routes) and TAM (PU), with trust serving as a crucial mediator, to explain university students' satisfaction and Continuance Usage Intention (CUI) of ChatGPT.
3) To conduct a multi-group analysis examining how weekly usage duration moderates the persuasive mechanisms within the ELM-TAM framework, specifically investigating whether the relative influence of central versus peripheral routes shifts as users transition from exploratory to habitual usage patterns.
4) To offer practical implications for both AI educators and developers, guiding the design of more effective and ethically sound AI tools and promoting responsible AI literacy among students in higher education.

Guided by the above objectives, this study addresses the following research questions:

RQ1: How do central route cues (e.g., IQ) and peripheral route cues (e.g., perceived fairness, accountability, transparency) jointly influence university students' trust in ChatGPT?

RQ2: What is the mediating role of trust and PU in influencing students' satisfaction and CUI towards ChatGPT?

RQ3: How does weekly usage duration moderate the relative influence of central route (IQ) and peripheral route (fairness, accountability, transparency) processing on students' trust formation, and what implications does this have for perceived usefulness, satisfaction, and CUI?

II. Literature Review and Hypothesis Development

A. Integrating ELM and TAM: A Bibliometric Perspective

To explore the integration of ELM and TAM in the context of generative AI, this study conducted a bibliometric analysis using the bibliometric R package. Previous scholars (e.g., Al-Emran and Arpaci [16–18] have demonstrated the value of bibliometric methods in mapping research trends and identifying gaps to guide theoretical development. To conduct the bibliometric analysis, the Web of Science (WOS) database was utilized as the primary data source. A Topic Search (TS) was conducted using a combination of keywords: ("Elaboration Likelihood Model" OR "ELM") and ("Technology Acceptance Model" OR "TAM"), resulting in the extraction of 24 articles. As illustrated in Fig. 1, refinement measures were applied to ensure the relevance and quality of the dataset. Following data cleaning, the final dataset consisted of 21 articles. This dataset was then exported and processed using the Bibliometric R package, a widely adopted tool for bibliometric analysis. The data analysis involved descriptive statistics, co-occurrence network construction, and thematic evolution mapping, thereby providing valuable insights into the conceptual and intellectual structure of research bridging the ELM and TAM frameworks.

The selected articles, published between 2010 and 2025, came from 19 sources, with a 4.73% annual growth rate. The sample involved 63 authors, with an average of 3 co-authors per article and a notable international collaboration rate of 52.38%. The average publication age was 4.86 years, and the average citation count was 51.76 per article, reflecting high scholarly impact. The dataset included 96 author keywords and 1677 cited references.

A three-field plot revealed that China led in publication output, with key themes including "ELM," "TAM," "source credibility," "ChatGPT," and "intention". These findings support the rationale for this study to integrate ELM and TAM into a unified theoretical framework, which can effectively capture both users' cognitive and emotional responses to AI tools like ChatGPT and explain their actual usage behavior.

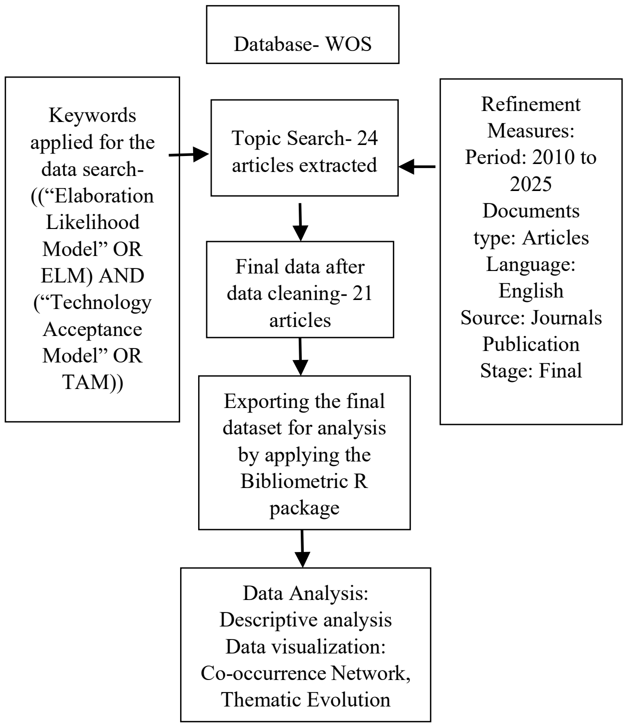

Fig. 1. Flowchart of search strategy, document selection for bibliometric analysis.

Keyword analysis revealed dominant terms such as "ELM", "TAM", "user acceptance", and "moderating role". Concepts like "perceived usefulness" and "source credibility" frequently emerged, pointing to continued reliance on TAM constructs and trust-based variables. These results underscore a convergence around affective-cognitive processing and Behavioral Intention (BI) in AI-related user studies.

The co-occurrence network analysis (see Fig. 2) reveals the conceptual structure and clustering patterns within the existing literature. The term "ELM" emerges as a central and highly connected node, frequently co-occurring with constructs related to both cognitive and affective processing, such as "moderating role", "source credibility", and "information quality". A distinct cluster is formed around the TAM, with strong associations to key constructs like "perceived usefulness" and "behavioral intention", reflecting its foundational role in technology adoption research. Importantly, "trust" and "perceived usefulness" function as bridging nodes between ELM and TAM, suggesting theoretical integration and complementarity in understanding users' engagement with generative AI tools. This network highlights a notable research gap—the limited synthesis of ELM and TAM frameworks—underscoring the need for integrated approaches to explain user behavior toward AI applications such as ChatGPT.

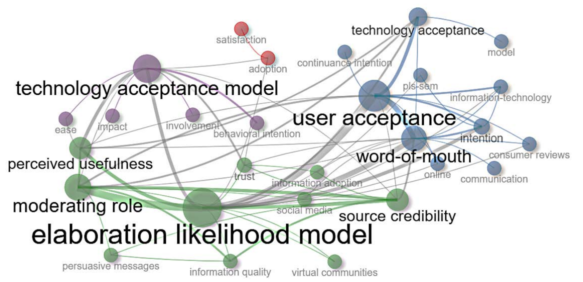

Fig. 2. Co-occurrence network.

Thematic evolution (see Fig. 3), segmented into four periods (2010–2017, 2018–2021, 2022–2024, and 2025), showed ELM dominance in early years, emphasizing persuasion and message processing. From 2018 onward, themes shifted toward user acceptance and moderating effects, with TAM gaining visibility from 2022, indicating increasing convergence. By 2025, ELM remained central, yet closely aligned with TAM, reflecting a maturing integration of persuasive communication and technology adoption theories.

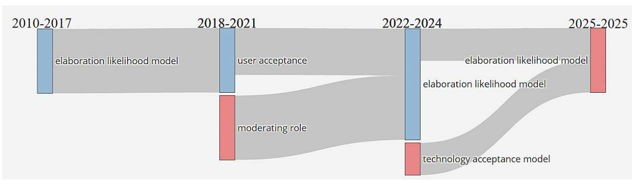

Fig. 3. Thematic evolution.

These findings underscore a critical research gap: while ELM and TAM have individually informed many studies, efforts to systematically integrate them—especially in the context of generative AI tools like ChatGPT—remain limited. This gap provides theoretical justification for the present study, which adopts an integrated ELM–TAM framework to investigate how cognitive, affective, and trust-related constructs jointly influence students' satisfaction and continued usage intention toward ChatGPT.

B. Elaboration Likelihood Model (ELM)

ELM, introduced by Petty [13], provides a framework to understand how individuals process persuasive messages. ELM divides information processing into two routes:

Central route—This route requires active and effortful processing. Individuals engaged through the central route carefully scrutinize the content of the message, such as the quality, accuracy, and relevance of the information. This type of processing leads to more durable attitude changes because it involves deep cognitive engagement with the content.

Peripheral route—This route involves low-effort processing where individuals rely on superficial cues such as attractiveness, reputation, or emotional appeal rather than the actual content of the message. While decisions made via the peripheral route might be quick and efficient, they are less stable and more susceptible to change.

When applied to ChatGPT, these two pathways help explain how students form perceptions of the tool. Academic users may rely on the central route to assess the quality and relevance of ChatGPT's responses, while casual or emotionally driven interactions may follow the peripheral route, influenced by the tool's perceived fairness, transparency, or ethical functioning.

C. Technology Acceptance Model (TAM)

TAM, introduced by Davis [19], has been widely employed to understand user adoption of technology, particularly in information systems. It posits that PU and PEOU are the two primary factors influencing user acceptance. PU refers to the degree to which a person believes that using a particular system would enhance their performance, while PEOU pertains to the degree to which the system is free from effort. The TAM model has proven to be robust in understanding how users decide whether or not to adopt new technologies.

In this study, PU is adopted as a key explanatory construct, while PEOU is excluded. Prior research suggests that PU has a stronger and more direct influence on BI, whereas the effect of PEOU is primarily indirect, mediated through PU [20]. Moreover, with the increasing simplicity and user-friendliness of digital interfaces, the predictive power of PEOU has declined [21].

Instead of PEOU, this study incorporates Trust as a core construct in the conceptual model. Additionally, Satisfaction is used to represent user attitudes, enabling an examination of its relationship with CUI. The following section presents the development of the research hypotheses.

D. Toward an Integrated ELM–TAM Framework for ChatGPT Adoption

TAM has been widely used to explain how students accept various technologies, including AI tools like ChatGPT. But the decision to use a tool isn't only about logic—it's also about how the tool makes students feel. That's why this study also draws on the ELM. ELM helps explain how students form judgments in two ways: sometimes through quick impressions, like whether the tool seems fair or transparent, and other times through deeper thinking about the quality and clarity of the information it provides [13]. Previous studies have shown that both types of thinking matter [22, 23]. Beyond the cognitive-affective duality captured by ELM and TAM, recent research has extended other established technology acceptance frameworks to the GenAI context, revealing a broader spectrum of influencing factors. For instance, drawing on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), Ayyoub *et al.* (2025) [24] investigated the drivers of GenAI acceptance among higher education educators in the Arab region. This UTAUT2-based evidence complements our ELM-TAM integration by affirming that adoption is shaped by a confluence of personal disposition (Personal Innovativeness), emotional experience (Hedonic Motivation), social context (Social Influence), and economic considerations (Price Value), factors that operate alongside the central and peripheral routes of persuasion.

This study positions Trust and PU as central predictors of students' Satisfaction Attitude, which in turn drives their CUI of ChatGPT. Trust reflects emotional confidence in the tool's reliability and ethical functioning [25], while PU captures students' belief that ChatGPT enhances their academic performance [8]. When students perceive the tool as both reliable and beneficial, their long-term engagement is more likely. Prior research has extended TAM by incorporating emotional constructs, demonstrating that trust and fairness perceptions significantly influence user satisfaction [8, 23, 26]. Moreover, Gen Z students—often digital natives—are especially receptive to adopting AI tools they deem emotionally trustworthy and academically supportive [27]. Given the increasing prevalence of AI in educational contexts, understanding both cognitive (usefulness) and affective (trust) drivers is essential for promoting sustainable usage.

Our integrated ELM-TAM framework offers a key theoretical advancement specific to the generative AI context. It theorizes and tests the distinct antecedents of trust by differentiating between cognitive evaluations (Central Route: IQ) and affective-heuristic evaluations (Peripheral Route: Fairness, Accountability, Transparency). In doing so, the model moves beyond treating trust as a monolithic outcome and instead delineates its specific formation routes. This is particularly critical for AI, where users must navigate system opacity. They may initially grant trust based on ethical perceptions (peripheral route), but must continually verify it through content quality (central route).

1) Peripheral route: Emotional evaluations of ChatGPT

The peripheral route involves evaluating ChatGPT based on emotional and non-cognitive factors. In research on users' perceptual evaluation of AI systems, fairness, accountability, and transparency have emerged as critical factors. Studies suggest that students' trust in AI tools like ChatGPT is often shaped by these emotional and ethical cues, even when users do not rigorously assess the IQ [28, 29]. For example, Praditomo *et al.* [27] found that students' continued use of ChatGPT is significantly driven by such emotional factors, which foster positive attitudes toward the tool. Consequently, peripheral cues can directly influence students' emotional engagement, shaping their satisfaction and long-term usage intentions.

Fairness, defined as the impartial and unbiased handling of user queries and content, significantly influences emotional trust in AI systems [29]. Unfairness perceptions erode emotional trust, creating resistance to continued use even when technical performance remains high [28, 30].

Transparency reflects the degree to which users comprehend how ChatGPT generates, selects, and presents information [29]. In black-box AI systems, opacity fosters suspicion, reducing users' willingness to continue engagement. Transparent AI, conversely, enhances emotional trust by aligning perceived system behavior with users' expectations of ethical responsibility [31].

Accountability denotes ChatGPT's perceived responsibility for the information it generates. When the system visibly owns errors, clarifies uncertainty, and demonstrates reliability, students' confidence strengthens [30]. In contrast, systems perceived as irresponsible provoke distrust and disengagement. Users are more likely to trust AI when they perceive it as answerable for its actions. Accountability becomes a crucial antecedent to building sustainable trust [29]. Accordingly, we propose:

H1: The peripheral route of ELM, including perceived fairness, perceived transparency, and perceived accountability of ChatGPT, positively influences students' trust in the tool.

2) Central route (information quality): Cognitive evaluations of ChatGPT

Studies have shown that IQ, information usefulness, and source trust are interrelated when using ChatGPT [12]. When students critically assess the accuracy, clarity, and relevance of the information provided by ChatGPT, they are more likely to perceive it as useful for academic tasks. This perception of usefulness, in turn, enhances their satisfaction and supports their continued use of the tool [32]. IQ, characterized by accuracy, richness, timeliness, format, and relevance, significantly impacts the PU and trust in ChatGPT. These factors, in turn, influence users' intention to continue using the tool [12]. When exploring higher education students' CUI of ChatGPT, the research proposed that IQ refers to the clear, accurate, up-to-date, and reliable qualities [33]. Hence, in this research, we proposed that the central route of ELM emphasizes the importance of IQ in shaping students' trust evaluations of ChatGPT. Furthermore, PU is a critical determinant of user acceptance [19]. In the context of ChatGPT, students are more likely to find the tool useful if it provides high-quality, relevant, and accurate information that supports their academic goals. When ChatGPT consistently delivers high-quality information aligned with students' academic expectations, it enhances PU. In light of this, we propose:

H2a: Information quality positively influences students' trust of ChatGPT.

H2b: Information quality positively influences students' perceived usefulness of ChatGPT.

3) Perceived usefulness and trust

Previous research examined whether IQ—measured across five dimensions—predicts PU and source trust, which in turn influence users' continuance intention to use ChatGPT. The findings demonstrated that when users perceive high-quality information, they are more likely to find the tool useful and trustworthy—two factors that subsequently enhance their willingness to continue using the system [12]. From the ELM perspective, other studies have also explored the relationships among trust, PU, and use intention [34]. Furthermore, empirical research conducted with university students found that trust plays a critical role in shaping behavioral intention, which subsequently influences actual usage of ChatGPT [4].

The TAM framework traditionally emphasizes PEOU and PU as key determinants of technology adoption. According to Davis [19], PU refers to "the degree to which a person believes that using a particular system would enhance their job performance." In the context of ChatGPT, PU indicates whether students believe the tool aids their academic performance, such as improving efficiency, accuracy, and the quality of their work. Trust, as an emotional and affective construct, can precede cognitive evaluations and influence how students assess the perceived utility of AI tools. Prior studies by Bhaskar *et al*. [23] and Gefen *et al*. [35] highlight that trust in technology is critical in shaping users' perceptions of PU.

In the context of ChatGPT and similar AI tools, students are more likely to continue using such systems when they perceive them as useful. However, as Ma [8] argued, the traditional factors within the TAM alone may be insufficient. Emotional cues, particularly trust, also play a pivotal role in user acceptance. Supporting this view, Abou-Shouk [15] identified trust as a key determinant in ChatGPT adoption.

Given these findings, trust serves as a critical bridging variable in this study's integrated model combining ELM and TAM. Specifically, trust replaces the original PEOU construct from TAM and is positioned as a central mediator between external factors and both user satisfaction and continuance intention. Accordingly, this study proposes the following hypothesis:

H3: Students' trust in ChatGPT positively influences their perceived usefulness of the tool.

4) *Satisfaction and continuance use intention*

According to Bhattacherjee [32], satisfaction arises when a system meets or exceeds the user's expectations, primarily shaped by their perceptions of usefulness and ease of use. In the case of ChatGPT, trust is likely a precursor to satisfaction, as it influences students' emotional responses and their overall experience with the tool.

Satisfaction can be conceptualized as an affective response or usage attitude within the TAM framework. In TAM, usage attitude has traditionally been linked to PU and PEOU represented in this study by trust. In academic environments, student satisfaction with AI tools like ChatGPT is shaped not only by the utility of the tool in achieving learning goals, but also by their emotional trust in its operation. Ma [8] found that trust in AI significantly enhances satisfaction, even when outputs may not be flawless. When students believe that ChatGPT provides academically relevant and ethically sound assistance, they are more likely to report a positive experience with the tool. Moreover, PU directly influences satisfaction, particularly when students recognize that the tool improves their learning efficiency or comprehension. As Davis [19] noted, users are more satisfied with systems they perceive as practically valuable. This relationship has been confirmed in multiple studies linking TAM and ELM constructs, where PU and trust jointly affect user satisfaction, which then drives loyalty or continuance intention [15, 36]. Satisfaction, therefore, functions as a critical affective response, shaped by both PU and trust. Based on these findings, we propose the following hypotheses:

H4: Students' trust in ChatGPT positively influences their satisfaction with the tool.

H5: Students' perceived usefulness of ChatGPT positively influences their satisfaction with the tool.

Within the TAM framework, users who perceive technology as useful and trustworthy are more likely to develop favorable attitudes, leading to higher satisfaction and stronger continuance intentions [19, 32]. For ChatGPT, when students feel that the tool reliably aids their learning and operates in a trustworthy manner, satisfaction becomes the pivotal predictor of ongoing engagement. Hence, the final hypothesis is proposed:

H6: Students' satisfaction with ChatGPT positively influences their intention to continue using the tool.

The conceptual framework guiding the study's hypotheses and analysis is illustrated in Fig. 4.

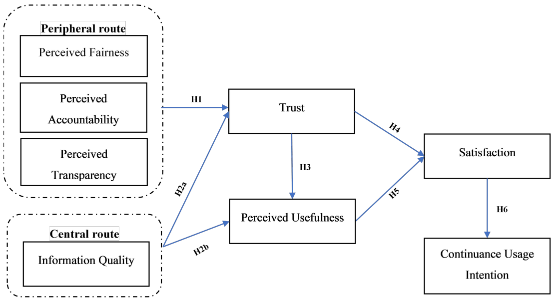

Fig. 4. Conceptual framework.

III. Methodology

A. *Data Collection*

In Vietnam, the adoption of ChatGPT has grown rapidly, marking significant progress in both educational and technological domains [37]. Therefore, this study selects Vietnamese higher education students as the target population for the survey.

The data utilized in this research were acquired through a structured online survey that was open for responses from March 29 to April 29, 2025. The survey was distributed to undergraduate, master's, and doctoral students within Vietnam's higher education system. To ensure the relevance of responses, participants must have used ChatGPT for at least one month before completing the survey. A combination of convenience sampling and purposive filtering will be applied to reach students who actively engage with AI tools as part of their learning activities. This approach ensures that the data reflects genuine experiences and informed judgments in the context of education.

B. *Survey Design*

The questionnaire was carefully constructed by adapting established scales from prior scholarly work to the context of AI-facilitated learning. Each construct in the model is operationalized through multiple items, and participants were asked to rate their agreement on a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

Special attention was paid to the phrasing of the items to ensure they resonated with students' real experiences of using ChatGPT in academic tasks, rather than remaining abstract or theoretical. Additionally, participants' socio-demographic information, including gender, age, and years of ChatGPT development experience, was collected.

However, we acknowledge a fundamental limitation in relying solely on self-reported perceptual data, a point underscored by recent research. Noroozi *et al.* (2025) [38] directly question the assumption that "perception means learning," finding no significant relationship between students' perceived learning and their actual performance in an online educational setting. Their study demonstrates that students' self-evaluations of learning can be misaligned with objective measures of their achievement. This misalignment suggests that constructs like Perceived Fairness, Transparency, and Accountability, which are inherently abstract and subjective, may be difficult to capture accurately through surveys alone. Learners might rely on socio-emotional experiences rather than a purely cognitive assessment when forming these perceptions [38]. Therefore, this study explicitly positions its findings as mapping the subjective user experience—the "felt" fairness and "perceived" transparency—rather than making definitive claims about the AI's objective qualities. This perspective is not a weakness but a necessary clarification of the scope of our data.

C. *Operational Definitions and Measurements*

A substantial portion of existing research on AI in education primarily focuses on the technical performance of these systems, typically assessed through indicators such as accuracy and reliability, rather than on their broader pedagogical implications [39]. However, this emphasis often overlooks a more personal dimension, namely how students perceive and experience AI tools. Key perceptions such as fairness, transparency, accountability, and IQ are frequently examined in isolation rather than as interrelated components of a unified user experience.

Following the scenario, participants were requested to complete a questionnaire that evaluated their perceptions and assessments of the scenario. The questionnaire incorporated eight reflective constructs: Perceived Fairness, Perceived Accountability, Perceived Transparency, Information Quality, Trust, Perceived Usefulness, Satisfaction, and Continuance Usage Intention.

To assess these constructs, we adapted items from established scales [28, 33, 40–46] to fit the specific context of this study (see Table A1). Each construct was operationalized with reference to validated academic sources, with minor adaptations to fit the specific context of this study. All measurement items were adapted thoughtfully to preserve their theoretical meaning while fitting the specific context of AI use in education.

The questionnaire was created in English and then translated into Vietnamese. Both the translation and back-translation were independently reviewed by experts and university professionals to make sure the items were accurate, consistent, and culturally appropriate.

D. *Data Analysis*

The study used SPSS for descriptive and demographic analyses, while SmartPLS was employed for SEM to examine the hypothesized relationships among constructs. SEM is particularly suitable for this study's aims, given its strength in handling complex relationships among latent variables, especially when integrating dual-path theoretical frameworks such as the ELM and the TAM [47].

The analysis will proceed in two phases. First, the measurement model will be assessed to ensure reliability (via Cronbach's alpha and composite reliability), convergent validity (via Average Variance Extracted), and discriminant validity. Once satisfactory measurement properties are established, the structural model will be evaluated by examining path coefficients, effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 5000 resamples will be used to test the significance of the hypothesized paths. This analytic strategy provides a robust framework for understanding not just whether, but how and why students choose to continue engaging with ChatGPT as a learning tool.

It is crucial to interpret the results of this structural model within the context of the nature of our data. The structural model reveals relationships between perceptions; it does not confirm that these perceptions are accurate reflections of the AI's objective properties or their direct impact on tangible learning gains. Future research could strengthen these findings by triangulating self-report data with behavioral data or objective performance metrics.

IV. RESULTS

A. *Sample Profile*

Table 1. Demographic characteristics of the respondents (N = 359)

Variable	Descriptive	Frequency	Percentage
Gender	Male	174	48.5%
	Female	182	50.7%
	Others	3	0.8%
Age (Years old)	18–21	171	47.6%
	22–25	96	26.7%
	26–30	56	15.6%
	31–35	21	5.8%
	Above 35	15	4.2%
Education Level	Bachelor	290	80.8%
	Master	55	15.3%
	PhD	14	3.9%
Field of Study	Business/Management/Marketing	132	36.7%
	Social Sciences	44	12.2%
	Education	30	8.4%
	Engineering/IT	75	20.9%
	Health Sciences	21	5.8%
	Humanities	22	6.1%
	Natural Sciences	35	9.7%
Weekly Usage Duration	< 1 hour	91	25.3%
	1–2 hours	88	24.5%
	2–3 hours	90	25.1%
	> 3 hours	90	25.1%
ChatGPT Version Used	Free version	280	78.0%
	Premium version	79	22.0%
Duration of ChatGPT Use for Academic Purposes	1–2 months	52	14.5%
	2–4 months	80	22.3%
	> 4 months	227	63.2%
Main Purpose of Use	Explain concepts	242	67.2%
	Help with assignments	235	65.3%
	Generate ideas	188	52.2%
	Exam preparation	179	49.7%
	Find references	210	58.3%
	Summarize materials	165	45.8%
	Edit academic writing	205	56.9%
	Support research activities	176	48.9%

Table 1 outlines the demographic profile of the 359 Vietnamese university students who participated in this study. Female students made up a slightly larger portion of the sample (50.7%) compared to male students (48.5%). The majority were within the typical university age range, with 47.6% aged 18–21 and 26.7% aged 22–25. Most of them were pursuing a bachelor's degree (80.8%), while a smaller proportion were enrolled in master's (15.3%) or doctoral programs (3.9%). Academically, students were primarily concentrated in business, management, and marketing

(36.7%), followed by those in engineering or IT (20.9%) and social sciences (12.2%). These figures indicate that ChatGPT use is particularly common among students whose academic disciplines require structured thinking, analytical tasks, and written output.

When it comes to how students use ChatGPT, most accessed the free version (78.0%), while about one in five used the premium version (22.0%). More than half (63.2%) had been using it for over five months, which shows that it has become part of their study habits. Weekly usage was fairly even, with about a quarter using it for more than three hours per week and another quarter using it for less than an hour. The most common uses were to help with assignments (65.3%), explain concepts (67.2%), and find references (58.3%). These results show that students turn to ChatGPT not just for quick help, but also to support deeper learning and academic work across different subjects.

B. Common Method Variance

Since this study used self-reported responses, it was important to ensure the data were free from bias. Harman's single-factor test with Principal Axis Factoring showed that the first factor accounted for 47.329% of the total variance—below the 50% threshold—indicating that Common Method Variance (CMV) is not a threat. According to Baumgartner and Weijters [48], if the value of CMV is below 50%, it indicates that CMV is not a concern and that there is consistency in the responses to the research instrument. To complement this, the Variance Inflation Factor (VIF) was also assessed, with values ranging from 1.703 to 3.913, all well within the acceptable cut-off of 5. These findings collectively support the conclusion that the dataset is free from serious methodological issues and is suitable for continued analysis.

C. Results from SEM

1) Validity and reliability assessment

The results shown in Table 2 highlight that the measurement model meets the necessary standards for convergent validity and reliability. Following the guidelines by Hair *et al*. [49], four main criteria were used to assess this: all Outer Loading (OL) values are above 0.70, meaning each item strongly reflects its intended construct. Cronbach's Alpha (CA) values are also above 0.70, indicating good internal consistency among the items. Composite Reliability (CR) values exceed the same threshold, confirming that the constructs are measured reliably, and all Average Variance Extracted (AVE) values are above 0.50, showing that each construct explains a sufficient amount of variance from its indicators. Altogether, these results confirm that the model is both valid and reliable.

PR is evaluated as a second-order compound, divided into three PT, PF, and PA dimensions. Each dimension has four questions. Therefore, to conclude the assessment of the research method, Table 3 shows the validity of the formative model (compound model).

We initially evaluated collinearity in accordance with suggested formative assessment methodologies [50–52]: There were no multicollinearity issues, since the VIF values varied from 1.485 to 1.845, much below the conservative criterion of 3.3 [53]. Next, we used 5000 bootstrap resamples to analyse the significance and relevance of the indicators. PF = 0.436, PA = 0.414, and PT = 0.369 were the outer weights. All of these were statistically significant (t = 3.426–4.954; p < 0.001), with 97.5% confidence intervals that excluded zero, indicating that each first-order construct contributes significantly to PR in a unique manner. PF has the highest relative importance, followed by PA and PT. Overall, our findings support the validity of PR as a second-order formative concept and meet important formative-evaluation requirements [51, 54].

Table 2. Convergent validity and reliability

Construct	Items	OL	CA	CR	VIF	AVE
Peripheral Route (PR)	PA	0.858	0.761	0.863	1.517	0.678
	PF	0.900			1.485	
	PT	0.881			1.845	
Central Route (CR)	IQ1	0.917	0.927	0.948	3.738	0.820
	IQ2	0.904			3.111	
	IQ3	0.884			2.797	
	IQ4	0.911			3.602	
Perceived Usefulness (PU)	PU1	0.865	0.903	0.932	2.512	0.774
	PU2	0.899			2.928	
	PU3	0.877			2.430	
	PU4	0.879			2.586	
Trust (T)	T1	0.895	0.906	0.934	2.847	0.780
	T2	0.882			2.672	
	T3	0.877			2.561	
	T4	0.879			2.574	
Satisfaction (S)	S1	0.905	0.929	0.950	3.343	0.825
	S2	0.914			3.429	
	S3	0.890			2.911	
	S4	0.924			3.913	
Continuance Usage Intention (CUI)	CI1	0.903	0.920	0.943	3.153	0.807
	CI2	0.904			3.169	
	CI3	0.884			2.795	
	CI4	0.902			3.230	

Notes:
a. OL, Outer Loadings; CA, Cronbach's Alpha; CR, Composite Reliability; AVE, Average Variance Extracted.
b. The threshold for OL > 0.70; CA > 0.70; CR > 0.70 and AVE > 0.50.

Table 3. Evaluation of the formative construct (peripheral route)

First-Order Constructs	Outer Weights	VIF	T value	P value	97.5% CI
PA	0.414	1.517	4.099	0.000	0.603
PF	0.436	1.485	4.954	0.000	0.605
PT	0.369	1.845	3.426	0.001	0.574

Significant at 0.001 (p < 0.001) level based on 5000 bootstraps. Collinearity statistic: VIF.

Table 4. Discriminant validity of Fornell-Larcker criterion and HTMT

Construct	(1)	(2)	(3)	(4)	(5)	(6)
Continuance Usage Intention (1)	**0.898**					
Central Route (2)	0.409 (0.443)	**0.905**				
Peripheral Route (3)	0.610 (0.730)	0.550 (0.654)	**0.823**			
Perceived Usefulness (4)	0.641 (0.703)	0.471 (0.512)	0.679 (0.818)	**0.880**		
Satisfaction (5)	0.577 (0.623)	0.547 (0.590)	0.687 (0.818)	0.635 (0.691)	**0.909**	
Trust (6)	0.631 (0.692)	0.524 (0.572)	0.689 (0.830)	0.614 (0.675)	0.551 (0.600)	**0.883**

Notes:
a. The parentheses values represent HTMT and the threshold of < 0.90 indicating weak and < 0.85 indicating strong validity.
b. The bolded values represent the square root of AVE.
c. Other values represent intercorrelations between constructs for measuring the Fornell-Larcker criterion.

Discriminant validity in this study was thoroughly assessed using three complementary approaches. The first involved the Fornell-Larcker Criterion, which compares the square root of each construct's AVE with its correlations to other constructs [55]. The findings indicate that all AVE square roots (bolded diagonals) are greater than their corresponding inter-construct correlations, supporting the presence of discriminant validity. The second method applied the HTMT ratio, following the recommendation of Henseler *et al*. [56], where values below 0.85 reflect strong discriminant validity. The results confirm that all HTMT values (displayed in parentheses) fall below this threshold, indicating satisfactory construct separation. Lastly, the cross-loading analysis was conducted by comparing each item's outer loading on its intended construct with its loadings on other constructs. In line with Hair *et al*. [49], the results show that all items load more strongly on their respective constructs than on others, providing further evidence that discriminant validity is not an issue. Together, these three methods confirm that the model exhibits robust discriminant validity, as detailed in Table 4 and Table 5.

Table 5. Discriminant validity of cross-loadings matrix

Items	CUI	CR (IQ)	PR	PU	Satisfaction	Trust
CI1	0.903	0.341	0.562	0.580	0.540	0.544
CI2	0.904	0.366	0.545	0.568	0.526	0.552
CI3	0.884	0.390	0.553	0.584	0.510	0.603
CI4	0.902	0.373	0.532	0.570	0.493	0.571
IQ1	0.374	0.917	0.496	0.407	0.498	0.464
IQ2	0.360	0.904	0.501	0.429	0.474	0.519
IQ3	0.397	0.888	0.493	0.484	0.523	0.434
IQ4	0.348	0.911	0.492	0.382	0.487	0.479
PA	0.556	0.381	0.804	0.581	0.592	0.555
PF	0.441	0.460	0.812	0.478	0.527	0.559
PT	0.510	0.515	0.851	0.616	0.578	0.586
PU1	0.563	0.372	0.595	0.865	0.514	0.482
PU2	0.586	0.421	0.589	0.899	0.569	0.558
PU3	0.565	0.446	0.613	0.877	0.594	0.587
PU4	0.541	0.414	0.581	0.879	0.553	0.524
S1	0.516	0.506	0.636	0.564	0.905	0.516
S2	0.545	0.479	0.633	0.596	0.914	0.487
S3	0.521	0.489	0.637	0.552	0.890	0.494
S4	0.514	0.515	0.596	0.597	0.924	0.505
T1	0.608	0.448	0.627	0.571	0.492	0.895
T2	0.567	0.471	0.576	0.548	0.458	0.882
T3	0.520	0.455	0.624	0.525	0.498	0.877
T4	0.533	0.480	0.605	0.524	0.497	0.879

Notes: The values printed in italic are the outer loadings.

2) *Hypothesis testing*

Fig. 5 and Table 6 summarize the hypothesis testing results, structured around the ELM that distinguishes between peripheral cues, central cues, and downstream user evaluations. In the peripheral route, three variables—perceived fairness (H1: $\beta = 0.574$, $p < 0.001$), perceived accountability, and perceived transparency are found to significantly influence trust. This demonstrates that students are not indifferent to the ethical dimensions of AI communication. When ChatGPT is viewed as fair, responsible, and transparent, users respond by forming stronger trust. These results emphasize that trust in ChatGPT is not solely a product of performance, but is also anchored in perceived moral and procedural legitimacy.

Meanwhile, on the central route, IQ significantly predicts both trust (H2a: $\beta = 0.210, p < 0.001$) and PU (H2b: $\beta = 0.206$, $p < 0.001$). This indicates that well-organized, relevant, and context-sensitive content from ChatGPT is not only seen as accurate but also instrumental in supporting academic problem-solving. When students perceive the content as coherent and tailored to their needs, they not only trust the tool more but also view it as a valuable academic partner—especially in tasks involving understanding concepts, summarizing materials, or generating learning insights.

From the evaluative outcomes, trust strongly increases PU (H3: $\beta = 0.506$, $p < 0.001$), suggesting that emotional assurance is a prerequisite for recognizing functional benefits—students only find ChatGPT useful when they first feel it is reliable. Trust also contributes to satisfaction (H4: $\beta = 0.258$, $p < 0.001$), but to a lesser extent than PU (H5: $\beta = 0.477$, $p < 0.001$), which means students derive greater satisfaction when ChatGPT actually helps them complete their academic goals, not just when it earns their confidence.

Finally, satisfaction has the strongest effect on CUI (H6: $\beta = 0.577$, $p < 0.001$), underscoring that the desire to keep using ChatGPT depends on how satisfied students feel with its ability to enhance academic experiences. Rather than novelty or ease of use alone, it is the actual success in meeting their goals through interaction with ChatGPT that explains the students' willingness to return.

Fig. 5 also reports the R^2 values, indicating the model explains a significant percentage of the variance in the endogenous constructs. The proposed model's R^2 values for CUI (0.333), PU (0.407), S (0.445), and T (0.506) meet the moderate to considerable levels set by Hair *et al.* [57], demonstrating adequate explanatory power. Chin [58] defines R^2 values of 0.33 or higher as relevant in social science research, indicating that the current findings corroborate the structural model's robustness.

In addition to the R^2 results, examining the effect sizes f^2 (Table 6) provides deeper insights into the differential impacts of the predictors. Cohen's (2013) [59] criteria (0.02 = small, 0.15 = medium, 0.35 = large) indicate that the routes PR → T ($f^2 = 0.467$) and S → CUI ($f^2 = 0.498$) have substantial effects as they exceed the 0.35 threshold. The route PU → S ($f^2 = 0.256$) is between 0.15 and 0.35, indicating a medium influence, whereas CR → PU ($f^2 = 0.052$) and CR → T ($f^2 = 0.062$) are above 0.02 but below 0.15, showing relatively moderate impacts. These findings indicate that the Peripheral Route is the key driver of Trust, and Satisfaction significantly increases Continuance Usage Intention, but the Central Route's contributions are modest.

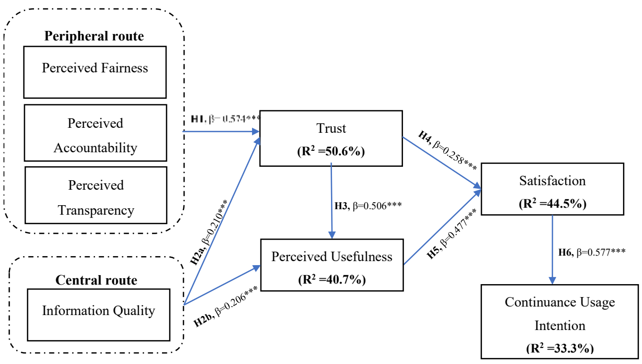

Fig. 5. Hypothesis summary.

Beyond explanatory power, the study also examined the model's predictive validity to assess how well it can predict new observations [60]. The model's predictive relevance was evaluated using the PLSpredict technique in SmartPLS 4.

The study confirms predictive validity by finding that all endogenous constructs have Q^2 predict values larger than zero, as stated by Shmueli [60]. Specifically, PU (0.396), S (0.424), and T (0.485) show great predictive relevance, but CUI (0.228) shows intermediate relevance. The model thus demonstrates both high explanatory power (R^2) and strong external predictive validity.

Several PLS-SEM diagnostics were used to measure global model fit [53, 56]. The Standardized Root Mean Square residual (SRMR) value for the saturated model was 0.038, and for the estimated model, it was 0.131. The saturated model's SRMR of 0.038 is significantly below the suggested threshold of 0.08 [56, 61], which indicates a satisfactory model fit (Table 7). The precise fit indices d_ULS (saturated = 0.398; estimated = 4.764) and d_G (saturated = 0.286; estimated = 0.451) were compared to their bootstrap-based confidence intervals, which indicated that the original values were within acceptable limits [62]. Finally, the Normed Fit Index (NFI) for the saturated model was 0.912, and for the estimated model, it was 0.878, both of which are near the required cutoff of 0.90, indicating that the model is of good quality [63].

Table 6. Summary of hypothesis testing

Hypothesis	Path Coefficient (β)	T statistic	Bootstrapping CI 97.5%		Conclusion
			Lower	Upper	
H1. Peripheral Route → Trust f2 = 0.467	0.574***	10.958	0.474	0.684	Supported
H2a. Central Route → Trust f2 = 0.062	0.210***	3.803	0.099	0.318	Supported
H2b. Central Route → PU f2 = 0.052	0.206***	3.844	0.099	0.309	Supported
H3. Trust → PU f2 = 0.313	0.506***	8.732	0.389	0.681	Supported
H4. Trust → Satisfaction f2 = 0.075	0.258***	4.037	0.130	0.381	Supported
H5. PU → Satisfaction f2 = 0.256	0.477***	7.236	0.351	0.610	Supported
H6. Satisfaction → CUI f2 = 0.498	0.577***	10.872	0.469	0.676	Supported

Notes: * indicates significance at the 0.05 level (< 0.05), and *** indicates significance at the 0.001 level ($p < 0.001$). These symbols represent the strength of evidence against the null hypothesis, with *** indicating a higher degree of statistical confidence.

Table 7. Model fit

Fit Index	Saturated Model	Estimated Model
SRMR	0.038	0.131
d_ULS	0.398	4.764
d_G	0.286	0.451
Chi2	606.456	844.296
NFI	0.912	0.878

D. The Moderating Role of Weekly Usage Duration of ChatGPT

1) Measurement Invariance Assessment (MICOM)

Consistent with the guidelines in [64], the measurement invariance of composites was tested using the MICOM procedure prior to the MGA, as reported in Table 8. Since the model specification was the same for both groups, step 1 (configural invariance) was established. While PU failed to meet the condition ($p = 0.002$) in Step 2 (compositional invariance), the majority of constructs (CUI, CR, PR, S, and T) did ($p > 0.05$). Despite this exception, the majority of structures exhibit configural and compositional invariance, indicating partial measurement invariance, which is deemed adequate for carrying out MGA. All constructs displayed non-significant differences ($p > 0.05$) in Step 3 (equality of means and variances), showing invariance across groups. All things considered, the findings are consistent with partial measurement invariance, which permits legitimate group comparisons of path coefficients.

Table 8. Summary of MICOM measurement invariance results (Step 2–3)

Construct	Step 2 Compositional Invariance (p-value)	Step 3a Equality of Means (p-value)	Step 3b Equality of Variances (p-value)
CUI	0.061	0.801	0.748
CR	0.509	0.338	0.848
PR	0.419	0.802	0.371
PU	0.002	0.565	0.834
Sat	0.064	0.842	0.565
Trust	0.209	0.862	0.270

Note: A p-value > 0.05 indicates no significant difference and thus invariance is established. Only PU failed in Step 2, suggesting partial measurement invariance.

To explore whether differences exist in students' behavioral patterns based on their ChatGPT usage, this study categorized participants according to their weekly usage duration. Specifically, the sample was divided into two groups: the "Less Group" ($n = 179$), consisting of students who used ChatGPT for less than two hours per week, and the "More Group" ($n = 180$), consisting of those who used it for more than two hours per week.

To better understand differences between the two groups, the mean scores of the original questionnaire items (measured on a 7-point Likert scale) were analyzed, and the results are presented in Table 9. Additionally, path comparisons between groups were conducted using Bootstrapping-based MGA. The results of this analysis are reported in Table 10.

Table 9. Mean scores of original questionnaire items (7-point likert scale)

Weekly Usage Duration	PF	PA	PT	IQ	T	PU	S	CUI
Less Group	5.046	5.425	5.088	4.898	5.137	5.394	5.149	5.229
More Group	5.094	5.203	5.190	4.740	5.160	5.307	5.181	5.192
Total	5.070	5.313	5.139	4.819	5.148	5.350	5.165	5.210

To assess measurement reliability and stability, the STDEV values derived from the bootstrapping process for both groups (Less Group: $N = 179$; More Group: $N = 180$) were examined. These values ranged from 0.064 to 0.098, all below the conventional threshold of 0.10 in PLS-SEM studies, indicating that the estimates are stable and the sampling distribution is consistent [65]. This supports the methodological validity of the MGA results.

Table 10. The results of multi-group analysis

Paths	Path Coefficient (β) Less Group (N = 179)	Path Coefficient (β) More Group (N = 180)	STDEV Less Group (N = 179)	STDEV More Group (N = 180)	p value Less Group (N = 179)	p value More Group (N = 180)	t value Less Group (N = 179)	t value More Group (N = 180)	p value 2-tailed (Less VS More Group)
H1. Peripheral Route→Trust	0.546***	0.593***	0.083	0.065	0.000	0.000	6.586	9.092	0.666
H2a. Central Route→Trust	0.291***	0.139*	0.085	0.070	0.001	0.046	3.421	1.993	0.164
H2b. Central Route→ PU	0.240**	0.178**	0.093	0.068	0.010	0.008	2.578	2.634	0.597
H3. Trust→ PU	0.540***	0.469***	0.098	0.072	0.000	0.000	5.498	6.564	0.550
H4. Trust→ Satisfaction	0.226*	0.233**	0.091	0.084	0.013	0.005	2.492	2.782	0.949
H5. PU→ Satisfaction	0.617***	0.375***	0.090	0.087	0.000	0.000	6.872	4.307	0.056
H6. Satisfaction→ CUI	0.690***	0.470***	0.064	0.078	0.000	0.000	10.744	6.053	0.030

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

2) Descriptive patterns across groups

Table 9 reveals an important pattern: despite higher usage frequency, the More Group reported slightly lower mean scores for IQ (M = 4.740) compared to the Less Group (M = 4.898). This counterintuitive finding provides initial evidence that heavier usage may be associated with more critical evaluations of ChatGPT's content quality—a pattern that aligns with ELM's prediction that central route processing intensifies with repeated exposure.

3) Central route effects: Weakening influence among experienced users

The multi-group comparison (Table 10) reveals a striking and theoretically significant pattern. Contrary to conventional ELM predictions, the influence of the central route on trust differed markedly between groups. For the Less Group, the path from central route to trust was statistically significant (β = 0.291, p < 0.001), indicating that lower-frequency users rely heavily on content quality as a key mechanism for building trust. For the More Group, while this path remained statistically significant (β = 0.139, p = 0.046), its magnitude was considerably weaker—less than half the strength observed in the Less Group. This dramatic attenuation suggests that IQ loses much of its persuasive power among experienced users. This finding challenges the conventional ELM assumption that experienced users engage in deeper central processing leading to stronger quality-trust linkages. Instead, our results suggest a process of central route erosion. As students increase their usage and critically scrutinize ChatGPT's responses over time, they accumulate experiences with problematic outputs, such as fabricated references, logical inconsistencies, or unverifiable claims (commonly termed "hallucinations"). These repeated exposures to content limitations appear to substantially weaken, though not entirely eliminate, the persuasive power of perceived IQ.

The peripheral route (H1), by contrast, remained strongly significant for both groups (Less: β = 0.546, p < 0.001; More: β = 0.593, p < 0.001), with no significant difference between them (p = 0.666). This suggests that emotional and ethical cues—fairness, accountability, transparency—maintain their influence regardless of usage experience, functioning as stable trust anchors even when cognitive evaluations become critical.

4) Downstream effects: Satisfaction and continuance intention

Furthermore, two structural paths showed significant group differences: PU → Satisfaction and Satisfaction → CUI. In the relationship between PU and Satisfaction, this was stronger in the Less Group (β = 0.617, p < 0.001) than in the More Group (β = 0.375, p < 0.001), with a two-tailed p-value of 0.056, approaching marginal significance. This suggests that utility perceptions translate more directly into satisfaction during early adoption, but diminish as users habituate. More importantly, the path from satisfaction to CUI was significantly stronger in the Less Group (β = 0.690) compared to the More Group (β = 0.470), with a significant difference of $\Delta\beta$ = 0.22 (p = 0.030). This indicates that satisfaction plays a more decisive role in sustaining engagement among novice users, whereas experienced users may continue usage based on other factors (e.g., habit, lack of alternatives) even when satisfaction plateaus.

These findings align with the ELM's dual-process framework, though with a significant departure from traditional expectations. ELM typically assumes that users with high involvement engage in deeper central processing, which should lead to more stable and enduring attitudes. Our results complicate this assumption. When central processing uncovers fundamental flaws in content quality, it appears to generate skepticism rather than trust. Students in the Less Group, who are still familiarizing themselves with ChatGPT, seem to evaluate its outputs with a degree of openness—if the information appears clear and relevant, they tend to accept it as trustworthy. By contrast, students in the More Group have had enough exposure to identify recurring problems: fabricated citations, plausible-sounding but inaccurate claims, and a general lack of verifiability. Their engagement is no less cognitive—in fact, it represents authentic central route processing—but the conclusion they arrive at is not confidence but wariness. Once students recognize that IQ cannot be reliably trusted, its power to persuade effectively collapses.

V. Discussion

This study offers several critical insights into the factors driving the continued use of ChatGPT among Vietnamese university students by integrating the ELM and the TAM. Our findings highlight the crucial interplay between emotional, peripheral cues and cognitive, central evaluations of IQ and usefulness, mediated by trust, and reveal significant moderating effects of usage duration.

The demographic profile of the participants offers important context for understanding how students interact with ChatGPT. A significant majority of participants were bachelor's students (80.8%), with master's (15.3%) and PhD students (3.9%) making up a smaller portion. This composition may partly explain why peripheral cues such as fairness and transparency had stronger effects than central content-based evaluations for the overall sample. Undergraduate students, typically having less academic experience, may rely more on intuitive trust signals rather than engage in critical assessment of AI responses. Interestingly, although PhD students represented a small segment, they exhibited a stronger link between usage intention and actual behavior, suggesting that advanced academic exposure may foster more confident and purposeful engagement with AI tools. Age-wise, nearly three-quarters of respondents were under 25 (47.6% aged 18–21 and 26.7% aged 22–25), reflecting a digitally native population generally open to AI-driven assistance. Regarding fields of study, the largest group came from Business, Management, and Marketing (36.7%), followed by Engineering/IT (20.9%), which may influence how students frame the utility and trustworthiness of AI systems based on discipline-specific norms. Moreover, ChatGPT usage was fairly evenly spread across weekly durations, with a notable majority (78.0%) using the free version, potentially influencing satisfaction levels and perceptions of limitations. These demographic nuances underscore that student background—particularly educational level and academic discipline—shapes not only how ChatGPT is used, but also how it is perceived and evaluated in terms of usefulness, trust, and satisfaction.

The findings reveal that trust is significantly shaped by students' perceptions of ChatGPT's ethical behaviour, specifically fairness, accountability, and transparency. Among these peripheral cues, fairness and accountability stood out as particularly influential, indicating that students tend to trust ChatGPT more when they perceive it as fair and responsible in its responses. Transparency, while significant, appears less immediately salient, suggesting that students respond more strongly to visible cues of ethical conduct than abstract concepts. This aligns with the notion that fairness and accountability are more intuitively processed and readily observed during interactions, whereas transparency may be inferred rather than directly experienced. These findings reinforce the view that ethical judgments function as powerful peripheral routes in shaping user trust, particularly in everyday, low-effort interactions typical of tool-based learning environments.

Concurrently, the study confirms the importance of central-route processing, as IQ plays a meaningful role in driving both PU and trust. Students evaluate ChatGPT's usefulness based on the clarity, relevance, and structure of the content it provides. When responses are perceived as well-organized and aligned with academic needs, they reinforce the belief that ChatGPT is a dependable and effective academic assistant. Moreover, high-quality information not only supports functional value but also indirectly enhances emotional confidence in the tool. This illustrates how cognitive and affective evaluations are interlinked in shaping engagement.

Trust emerged as a pivotal construct connecting both ethical and informational evaluations to downstream outcomes. It not only fosters greater PU but also contributes to user satisfaction. This dual role of trust reflects its position as a psychological bridge that translates both intuitive and reasoned appraisals into a positive user experience. In line with existing literature, this suggests that trust is not merely a passive outcome but an active enabler of AI adoption, especially in contexts where users navigate uncertainty.

While both peripheral and central routes influence engagement, the findings suggest that ethical cues—particularly fairness and accountability—carry greater weight in students' continued use decisions. This pattern indicates that when cognitive involvement is relatively low, such as in time-constrained or outcome-driven academic tasks, students may rely more on intuitive judgments of credibility than deep evaluation of content quality. In such cases, perceived ethical alignment becomes the dominant driver of acceptance. This underscores the need for AI systems to not only perform well but also to be perceived as morally and procedurally sound in their interactions.

Moreover, satisfaction serves as the strongest determinant of students' intention to continue using ChatGPT. It integrates both emotional assurance and functional performance into an overall evaluation of experience. Students who are satisfied are more likely to develop habitual use patterns, suggesting that long-term engagement depends not just on trust or usefulness alone, but on the consistent delivery of a positive, value-adding experience. This reinforces the importance of designing AI tools that are not only intelligent but also relationally credible and experientially satisfying.

The PLS-MGA by weekly usage duration provided a nuanced and somewhat counterintuitive insight. While one might expect highly weekly usage to engage more deeply in central route processing, our results show the opposite pattern concerning trust formation. The findings reveal that the central route (IQ) significantly predicts trust in both groups but has a notably stronger effect among users with shorter usage duration. This, combined with the observation that the More Group reported a slightly lower average perception of IQ (M = 4.740) compared to the Less Group (M = 4.898), suggests a process of *central route erosion*: as students increase their exposure to recognizing ChatGPT's limitations, such as factual inaccuracies or 'hallucinations', more frequently. These repeated encounters may lead to a central negative attitude change [13, 66], thereby lowering their trust in ChatGPT despite frequent usage. This implies a heightened critical stance among experienced users, where IQ no longer solely drives trust. In contrast, participants with lower weekly usage, potentially still in the early stages of exploring the tool, may rely more surface-level cues or initial positive experiences, leading to more favorable yet superficial evaluations of IQ. This highlights that the relationship between usage experience and processing routes is not linear and can be negatively moderated by the tool's perceptible flaws.

Furthermore, significant group differences were observed for the paths from PU → Satisfaction and Satisfaction → CUI. The influence of satisfaction on CUI was notably stronger in the Less Group compared to the More Group. This suggests that for students with lower usage duration, satisfaction plays a more pivotal role in shaping their intention to continue using ChatGPT. This aligns with the notion that initial positive experiences and novelty are strong drivers for early adopters. However, for students with higher weekly usage, while satisfaction is still important, its marginal utility in driving continuance may diminish as they become more familiar and possibly encounter the tool's limitations. This nuanced understanding of behavioural differences across user subgroups is a key theoretical contribution, emphasizing that the drivers of AI adoption evolve with usage experience.

While this study successfully demonstrates the dual-path mechanisms driving ChatGPT adoption through the integration of ELM and TAM, it is crucial to acknowledge that understanding student engagement with generative AI extends beyond TAM frameworks. Recent scholarship has increasingly emphasized that GenAI adoption is not merely about trust and usefulness, but involves more nuanced considerations, including epistemic trust, accountability in knowledge production, and the evolving nature of human-AI collaboration in educational contexts [67].

From our multi-group analysis is the paradoxical finding that students with higher weekly usage reported lower information quality scores and showed no significant relationship between the central route (IQ) and trust. This pattern aligns with growing evidence that frequent users of ChatGPT encounter what Banihashem *et al.* (2025) [67] term "artificial cognition" limitations—specifically, AI hallucinations, fabricated references, and responses that appear logically coherent but lack factual grounding or verifiable sources.

This finding suggests a more complex narrative than simple technology acceptance: students may continue using ChatGPT not because they fully trust its outputs, but because they have learned to navigate its limitations—a form of pragmatic adoption rather than genuine acceptance. This resonates with concerns raised by scholars about the potential for GenAI to undermine critical thinking if students rely too heavily on AI-generated content without developing the evaluative skills necessary to identify inaccuracies or logical inconsistencies [67].

Our findings also point to an important evolution in how we conceptualize AI's role in education. Rather than viewing ChatGPT solely as an independent tool to be adopted or rejected, emerging frameworks propose understanding it as part of a "hybrid intelligent feedback" system where human and artificial cognition complement each other [67]. In this paradigm, GenAI feedback and human feedback are not competitive but complementary sources, each contributing unique strengths to the learning process. This hybrid model directly addresses the limitations our study uncovered, offering a pathway to mitigate risks like hallucinations and a lack of critical depth by integrating human oversight.

VI. Conclusion, Limitation, and Future Research

This study offers a deeper understanding of the factors shaping university students' continued use of AI-based tools in academic contexts by integrating ELM and the TAM. The findings underscore the dual importance of ethical cues (fairness, accountability, transparency) and content quality (information usefulness) in influencing students' trust, satisfaction, and engagement with ChatGPT. Trust plays a central role in translating both peripheral and central evaluations into meaningful outcomes, while satisfaction emerges as the most consistent predictor of CUI. This highlights that fostering sustained AI use in education requires more than technical reliability—it necessitates an ethically grounded, experientially satisfying interaction that meets both emotional and academic needs.

The PLS-MGA analysis revealed that weekly usage duration significantly moderates key relationships within the model. A pivotal finding is that while the central route (IQ) significantly builds trust across both user groups, its magnitude is substantially stronger for low-frequency users than for high-frequency users. This pronounced attenuation suggests that as students gain experience with ChatGPT and engage with its outputs, they become more critical of its IQ, and this cognitive evaluation ceases to be a primary driver of their trust. This phenomenon can be interpreted through the ELM as central route erosion or central negative attitude change, where deeper scrutiny of the tool's outputs reveals limitations that undermine trust.

A. Managerial and Practical Implications

The findings of this study offer several significant implications for AI developers and educators, as well as tailored recommendations for engaging novice and experienced users of ChatGPT.

For AI Developers: Developers of AI tools like ChatGPT must address the heightened sensitivity of high-duration users to IQ, authenticity, and transparency. Enhancing features such as source attribution, citation verification, and third-party fact-checking may strengthen trust and persuasion, particularly under central route processing. Furthermore, the observed diminishing return of satisfaction for users with higher weekly usage suggests that relying on satisfaction alone may not ensure long-term user retention. To (re)build trust with this segment, developers must prioritize features that enhance verifiable credibility, such as integrating source attribution, citation verification, and confidence indicators for AI-generated statements. Furthermore, since satisfaction's influence on continuance intention diminishes for heavy users, long-term retention strategies must go beyond user satisfaction and focus on delivering consistent, verifiable value and transparency. Developers are encouraged to improve these by offering source citations, integrating fact-checking functions, or indicating confidence levels in AI responses. User segmentation and interface personalization based on usage duration and cognitive styles could also optimize user experience and reinforce continued usage (e.g., guiding free version users towards premium versions offering quality-assured content).

For Educators: In educational contexts, instructors should caution students against overreliance on ChatGPT's surface-level responses and foster critical information literacy and fact-checking skills to mitigate risks of referencing inaccurate content in academic work. Beginner users should be trained to develop basic evaluative skills—questioning sources, cross-checking facts, and recognizing when AI-generated content requires verification. This early-stage training can prevent over-reliance and prepare students to engage more critically as their usage increases. Advanced users need a deeper understanding of the mechanisms and limitations underlying AI-generated responses, including the technical reasons for hallucinations and the epistemic boundaries of large language models. This stratified approach to AI literacy can empower students to leverage AI effectively and responsibly.

Beyond stratified instruction, educators should actively foster what Banihashem *et al.* (2025) [67] term "hybrid intelligent feedback literacy". This involves teaching students to critically navigate between human and AI-generated feedback. Curricula should empower students to recognize the distinct strengths and weaknesses of each source, develop systematic validation strategies, and understand their own responsibility in the human-AI collaborative process—their "shared agency" in co-creating knowledge [67]. Implementing hybrid feedback systems, where AI-generated input must be evaluated and supplemented with human judgment, can effectively operationalize this literacy.

For Heavier, More Experienced Users: This user segment engages in deeper scrutiny, where repeated exposure has likely revealed limitations such as AI hallucinations or superficial logic. To rebuild and sustain their trust, generic assurances of quality are insufficient. AI developers should prioritize features that address the core of their skepticism:

Provenance and Source Disclosure: Integrate source attribution and citation features to allow users to verify the origin of information.

Uncertainty Cues and Confidence Scores: Implement visual or textual indicators that convey the AI's confidence level in its responses, signaling when information might be speculative or less reliable.

Transparent Error Handling: Design clear mechanisms for the AI to acknowledge its limitations, admit mistakes, and provide pathways for users to report inaccuracies. These features directly support the central route processing that these users naturally employ, transforming their critical scrutiny into a structured verification workflow rather than a source of distrust.

For Novice or Lighter Users: This group is more susceptible to both peripheral and central route persuasion. The goal here is to foster initial trust and responsible adoption while laying the groundwork for critical AI literacy.

Clear Value and Ethical Affordances: The interface should make the tool's usefulness immediately apparent and prominently display ethical cues (e.g., clear terms of use, privacy notices, statements on AI ethics) to leverage the peripheral route effectively.

Staged AI Literacy Integration: Educators should design learning activities that move from initial, safe-use scenarios (e.g., using ChatGPT for brainstorming or summarizing non-critical content) with clear expectation setting about its potential pitfalls, towards more advanced workflows that incorporate mandatory verification, fact-checking, and proper citation practice. This scaffolded approach nurtures users from passive consumers into critical collaborators with the AI.

Encourage Reflective Practice: Even in early adoption, students should be prompted to reflect on their interactions: "How did you verify this information?" "What would you do if this response were incorrect?" This metacognitive training prepares them for the transition from peripheral to critical central processing that our findings show emerges with experience.

B. Limitations and Future Directions

Despite its contributions, this study has several limitations. First, it focused solely on Vietnamese university students, representing a single cultural and educational context. This may limit the external validity of the findings, as cultural norms and educational systems could significantly influence students' perceptions of AI's fairness, accountability, and transparency, thereby altering their trust and acceptance mechanisms. Future research should therefore incorporate samples from diverse national and cultural backgrounds to enhance the generalizability and comparative insight of the findings.

Second, while the study captured the moderating role of usage duration, future studies should include additional contextual variables such as digital literacy, academic discipline, task complexity, and domain expertise. Examining their moderating effects on ethical and cognitive cues—such as trust and persuasion routes—in the decision-making process of AI adoption would provide a more granular understanding.

Furthermore, future models could incorporate psychological and social factors, such as emotional attachment, peer influence, and trust in AI developers, to offer a more nuanced understanding of the determinants of sustained AI usage behavior and to enrich the theoretical foundation of AI adoption research. This would help to build more comprehensive models that account for the multifaceted nature of human-AI interaction.

APPENDIX

Table A1. Measurement items and sources

Construct	Items
Perceived Fairness [40]	ChatGPT gives information in a fair and balanced way.
	I feel that ChatGPT treats all topics fairly when helping with my studies.
	I believe ChatGPT gives equal support to different students' needs.
	ChatGPT provides answers and help in a way that feels just and reasonable.
Perceived Transparency [41]	I can access a great deal of information that explains how ChatGPT supports my learning.
	I can see plenty of information about the reasoning behind ChatGPT's educational responses.
	I feel that the available information helps me understand how ChatGPT generates its answers for academic tasks.
	I receive clear explanations from ChatGPT when I ask complex academic questions.
Perceived Accountability	I often have to explain why I do my learning tasks regarding ChatGPT.

[28, 42, 43]	I often need to check and explain the information I use from ChatGPT in my academic work. I feel responsible for verifying the accuracy of ChatGPT's responses when completing my learning tasks. I believe I am accountable for ensuring that the information from ChatGPT is appropriate for my academic needs.
Information Quality [33]	Information provided by ChatGPT is clear. Information provided by ChatGPT is accurate. Information provided by ChatGPT is up-to-date. Information provided by ChatGPT is reliable.
Trust [44]	I believe that ChatGPT is trustworthy for completing my assessments. I trust the response quality of ChatGPT for completing my assessments. I am confident that the technology provider of ChatGPT is honest. Even if not monitored, I would trust the assessments could be done right with the ChatGPT functions.
Perceived Usefulness [45]	It is easy to learn how to use ChatGPT. It is easy to use ChatGPT to find product/service/brand information. It is easy to use the information provided by ChatGPT to select a product/service/brand. It is easy for me to become skillful at using ChatGPT.
Satisfaction [46]	My overall experience of using ChatGPT for learning was very satisfying. My overall experience of using ChatGPT for academic support was very pleasant. Using ChatGPT to assist my studies turned out to be a very good idea. Overall, my experience with using ChatGPT for educational purposes was absolutely delightful.
Continuance Usage Intention [46]	I intend to continue using ChatGPT for my learning rather than discontinue its use. I will keep using ChatGPT regularly to support my academic activities. I intend to continue using ChatGPT rather than switch to other alternatives. I intend to increase my use of ChatGPT for learning tasks in the future.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

K.A.T. and C.F.L. reviewed the background and literature review; T.H.L. and I.J.E. reviewed the methodology; C.F.L. and I.J.E. analyzed and interpreted the data; T.H.L. and K.A.T. analyzed the discussion and conclusion; K.A.T. wrote, reviewed, and edited the paper. All authors had approved the final version.

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