# Students' Continuance Intention to Use Generative Artificial Intelligence for Academic Purposes: An Extended Expectation-Confirmation Model from a Vietnamese University

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## Abstract

This study investigated why students continue using generative artificial intelligence (Generative AI) for academic purposes at the Interlingual Institute of Education, Nguyen Tat Thanh University. It extended the Expectation Confirmation Model with two SDT-informed perceptions (autonomy and competence) and two Generative AI characteristics (perceived intelligence and anthropomorphism). Survey data from 269 students with prior academic experience using Generative AI were analyzed using PLS-SEM. Results have shown that seven direct relationships were supported, while the usefulness – satisfaction path was marginal and the competence – usefulness path was not significant. The model explained 37.3% of the variance in continuance intention. Perceived usefulness was the strongest direct predictor, followed by satisfaction. The findings extended post-adoption research in an underexplored Vietnamese international higher education setting and suggested that universities should strengthen the academic value, user satisfaction, learner autonomy, and responsible use of Generative AI.

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## Keywords

Generative Artificial Intelligence; continuance intention; Expectation Confirmation Model; Self-Determination Theory; higher education.

## 1 Introduction

Generative Artificial Intelligence (Generative AI) has rapidly become part of higher education, especially after the public release of conversational tools such as ChatGPT, Gemini, Claude, and DeepSeek. Students use these tools to generate ideas, summarize readings, translate academic texts, draft essays, solve problems, and receive immediate explanations [1, 2]. At the same time, Generative AI can produce inaccurate, biased, or incomplete responses, which makes responsible and sustained use a central concern for educators [3].

Therefore, the educational value of these tools therefore depends not only on initial adoption but also on students' intention to continue using them after actual experience. In information systems research, continuance intention is explained by post-adoption evaluation, particularly confirmation of expectations, perceived usefulness, and satisfaction [4]. This perspective is suitable for Generative AI because students revise their expectations after using the tools in real academic tasks.

However, students' continued use is also shaped by motivational and technology-specific factors. Self-

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Determination Theory suggests that sustained learning engagement is supported when students experience autonomy and competence [5]. In addition, Generative AI differs from conventional educational technologies because students may perceive it as intelligent or human-like in interaction, which can influence how useful they find the system [6, 7].

The Interlingual Institute of Education (NIIE), Nguyen Tat Thanh University, offers bilingual programs in which students routinely study through English-medium instruction and use digital tools for independent learning, which makes it a relevant setting for examining academic Generative AI use. Although many NIIE students have used Generative AI for academic activities, their usage patterns vary from critical and purposeful use to passive dependence or discontinued use after encountering inaccurate outputs.

Accordingly, this study investigated the factors shaping students' continued use of Generative AI in academic settings. It tested an extended ECM that incorporated SDT-informed need perceptions and Generative AI-specific characteristics as antecedents of perceived usefulness. The study aimed to identify the key determinants, evaluate their direction and magnitude, and propose recommendations for effective, ethical, and sustainable technology-supported learning.

## 2 Theoretical Background and Research Model

### 2.1 Continuance Intention and Generative AI

Continuance intention is a post-adoption construct that explains whether users intend to keep using a technology after they have already experienced it [4]. Unlike initial acceptance which often rests on expectations, social influence, or curiosity, continuance intention is based on real interaction and retrospective evaluation [8]; continued use depends on whether the tool proves reliable, useful, and compatible with academic goals after repeated interaction [6].

Generative AI refers to AI-based systems capable of producing new content in response to user prompts [1, 2]. Its human-like language makes it valuable for immediate learning support, but it also calls for responsible use, in which students evaluate responses critically, verify information, and avoid treating generated outputs as a substitute for their own reasoning [2]. This study defines Generative AI as a category of prompt-based tools rather than a single software product because students may switch between ChatGPT, Gemini, Claude, DeepSeek, or similar systems depending on accessibility, language support, and task requirements, and the unit of analysis is the student's perceived experience with Generative AI for learning.

### 2.2 Expectation Confirmation Model

The Expectation Confirmation Model (ECM) is one of the most influential frameworks for explaining information system continuance [4]. According to the model, users compare their actual experience with a system against their prior expectations. When the actual performance meets or exceeds expectations, confirmation occurs. Confirmation then affects perceived usefulness and satisfaction, which in turn influence continuance intention.

Perceived usefulness is particularly central in the model. It reflects the degree to which students believe Generative AI improves their academic performance, productivity, or learning effectiveness [9]. Satisfaction refers to students' overall affective evaluation after using the tool [4]. Within this framework, perceived usefulness is the pivotal post-adoption judgment for Generative AI: if students perceive outputs as irrelevant, inaccurate, or difficult to apply to coursework, their intention to continue using the technology may decline even when the tool appears advanced or popular.

### 2.3 Self-Determination Theory

Self-Determination Theory (SDT) proposes that sustained motivation is supported by three basic psychological needs: autonomy, competence, and relatedness [5]. Because this study focuses on individual student-Generative AI interaction, it incorporates autonomy and competence as SDT-informed perceptions rather than testing the full SDT framework. Perceived autonomy refers to students' sense of control over how, when, and at what pace

they use Generative AI for learning, whereas perceived competence reflects their confidence in using these tools effectively for academic tasks [5]. Both constructs are specified as antecedents of perceived usefulness. This specification is informed by recent AI-supported learning research. Previous research found that perceived autonomy significantly predicted perceived usefulness, whereas perceived competence did not [10]. Meanwhile, another study linked both needs primarily to intrinsic motivation and satisfaction [11]. Relatedness and intrinsic motivation were not included because socially mediated learning and motivational processes were outside the scope of the present model.

2.4 Generative AI-Specific Characteristics

Generative AI differs from ordinary digital tools because users often evaluate it through cognitive-like and social-like attributes [6, 7]. Perceived intelligence refers to students' perception that the system can understand prompts, process information, generate relevant responses, and adapt to academic contexts [6]. Perceived anthropomorphism refers to the perception that the AI system communicates in a human-like manner [6]. Generative AI often uses conversational language, remembers context within a session, and responds with polite or supportive tones. Such human-like interaction may reduce psychological distance and make students feel that the system is approachable [6]. In academic contexts, anthropomorphism can make the tool resemble a tutor or learning companion. Nevertheless, findings on its effect remain mixed across contexts, so its role should be interpreted carefully [7].

2.5 Research Hypotheses and Proposed Model

Based on the integrated framework, this study proposes nine hypotheses concerning the antecedents of perceived usefulness (H1-H5), the core cognitive-affective mechanism of the ECM (H6-H7), and the behavioral outcome (H8-H9):

*H1. Perceived intelligence positively affects perceived usefulness.*

*H2. Perceived anthropomorphism positively affects perceived usefulness.*

*H3. Perceived autonomy positively affects perceived usefulness.*

*H4. Perceived competence positively affects perceived usefulness.*

*H5. Confirmation positively affects perceived usefulness.*

*H6. Confirmation positively affects satisfaction.*

*H7. Perceived usefulness positively affects satisfaction.*

*H8. Perceived usefulness positively affects continuance intention.*

*H9. Satisfaction positively affects continuance intention.*

The hypothesized model and its estimation results are presented in Figure 1 (Section 4.3).

## 3 Research Methodology

3.1 Research Design, Sample and Measurement

This study employed a quantitative cross-sectional research design. The target population consisted of students enrolled at NIIE who had prior experience using Generative AI tools for academic purposes. Because the sample was drawn through non-probability convenience and referral sampling from a single bilingual institute within one private university, the findings were interpreted as institution-specific evidence rather than as statistically representative of the broader Vietnamese higher education population.

The questionnaire was developed from established measurement scales and adapted to the Generative AI learning context. The final instrument included eight reflective constructs: confirmation, perceived usefulness, satisfaction, continuance intention, perceived intelligence, perceived anthropomorphism, perceived autonomy, and perceived competence. The measurement items were adapted from validated scales in prior information systems, AI, and educational psychology research [4-11], then refined through expert consultation and pilot testing. All indicators were measured on a five-point Likert scale.

Five experts in management, information systems, and educational psychology reviewed the draft questionnaire, and a pilot test with 67 eligible students confirmed acceptable Cronbach's Alpha values above 0.70 for all constructs, so the final 31-indicator questionnaire was retained. Participation was voluntary and anonymous,

and respondents confirmed prior academic experience with Generative AI. Data collection was conducted at the District 7 campus during the second semester of the 2025-2026 academic year (February to May 2026). The questionnaire initially generated 325 responses. After removing incomplete responses, ineligible cases, and low-quality submissions, 269 valid responses were retained for analysis. With eight reflective constructs and 31 indicators, this sample satisfied the 10-times rule and Cohen's minimum requirements for PLS-SEM.

3.2 Data Analysis Procedure

Excel was used for descriptive statistics and initial data screening. SmartPLS 4 was used to estimate the measurement and structural models through Partial Least Squares Structural Equation Modeling (PLS-SEM). After descriptive screening, common method bias was assessed through full collinearity variance inflation factor values [13]; the reflective measurement model was evaluated through outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, and the Heterotrait-Monotrait Ratio [12, 14]; and the structural model was assessed using inner variance inflation factor values, coefficient of determination, effect size, path coefficients, bootstrapping with 10,000 subsamples, specific indirect effects, total effects, and Importance-Performance Map Analysis [15]. Statistical significance was determined at $p \leq 0.05$.

## 4 Results and Discussion

4.1 Descriptive Findings and Measurement Model

Of the 269 valid respondents, 52.8% were male and 40.9% female (6.3% unanswered), distributed across all four study years; the smartphone was the most frequently used device for academic Generative AI activities (48.3%), followed by the laptop (34.9%), indicating that students primarily access these tools through personal mobile devices.

The reflective measurement model achieved satisfactory reliability and validity. Table 1 summarizes the measurement model, reporting for each construct the indicators, their outer loadings, and construct-level reliability and convergent validity statistics. Twenty-nine indicators recorded outer loadings above the recommended threshold of 0.708, while ANT1 (0.688) and CI4 (0.640) fell below this benchmark. Both indicators were retained primarily on content-validity grounds rather than on aggregate statistics alone [12]. ANT1 anchors the general perception of human-likeness in the anthropomorphism scale, and CI4, adapted from Jung and Jo [8], captures the recommendation facet of continuance intention – students' willingness to advocate Generative AI use to peers – which complements the self-use items CI1-CI3; removing either indicator would narrow the content coverage of its construct. A loading of 0.640 implies that CI4 shares only about 41% of its variance with its construct; the indicator therefore contributes conceptual completeness rather than statistical strength, while construct-level convergent validity and reliability remained adequate (see Table 1). Cronbach's alpha values ranged from 0.718 to 0.819, rho_a values from 0.723 to 0.821, rho_c values from 0.830 to 0.881, and *AVE* values from 0.550 to 0.659.

**Table 1** Measurement model assessment

| Construct | Indicators | Outer loadings (indicator order) | Cronbach's alpha | rho_a | rho_c | *AVE* |
|---|---|---|---|---|---|---|
| Perceived Intelligence (INT) | 4 items (INT1-INT4) | 0.767 / 0.823 / 0.761 / 0.711 | 0.768 | 0.784 | 0.850 | 0.588 |
| Perceived Anthropo-morphism (ANT) | 5 items (ANT1-ANT5) | **0.688** / 0.750 / 0.817 / 0.744 / 0.747 | 0.805 | 0.807 | 0.865 | 0.563 |
| Perceived Autonomy (PA) | 3 items (PA1-PA3) | 0.806 / 0.832 / 0.797 | 0.742 | 0.747 | 0.853 | 0.659 |
| Perceived Competence (PC) | 3 items (PC1-PC3) | 0.787 / 0.790 / 0.821 | 0.718 | 0.723 | 0.841 | 0.639 |
| Confirmation (C) | 4 items (C1-C4) | 0.775 / 0.835 / 0.816 / 0.794 | 0.819 | 0.821 | 0.881 | 0.649 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Perceived Usefulness (PU) | 4 items (PU1-PU4) | 0.722 / 0.752 / 0.713 / 0.779 | 0.727 | 0.727 | 0.830 | 0.550 |
| Satisfaction (SA) | 4 items (SA1-SA4) | 0.729 / 0.841 / 0.811 / 0.776 | 0.799 | 0.806 | 0.869 | 0.624 |
| Continuance Intention (CI) | 4 items (CI1-CI4) | 0.801 / 0.815 / 0.767 / **0.640** | 0.751 | 0.765 | 0.843 | 0.576 |

*Note:* Outer loadings are listed in indicator order; the two values below the 0.708 benchmark (ANT1 = 0.688 and CI4 = 0.640) are shown in bold and examined in the text.

The Heterotrait-Monotrait Ratio matrix was reported in Table 2. Twenty-seven of the 28 construct pairs were below the stricter 0.85 guideline. The theoretically adjacent confirmation – satisfaction pair reached 0.911, exceeding both the 0.85 and the more permissive 0.90 guidelines. Three considerations support treating the two constructs as empirically distinguishable while acknowledging their overlap. First, the two constructs are theoretically adjacent in ECM [7]. Second, the bootstrap percentile interval of this pair, [0.835, 0.981], excluded 1, supporting empirical distinctness [14]. Third, the Fornell-Larcker criterion was satisfied for all eight constructs, including this pair, whose latent correlation of 0.742 remained below the square roots of the corresponding *AVE* values (0.805 for confirmation and 0.790 for satisfaction). Full collinearity variance inflation factor values ranged from 1.671 to 2.710, all below 3.3, suggesting that common method bias was not a serious threat [13].

**Table 2** Heterotrait-Monotrait Ratio matrix

| HTMT | ANT | CI | C | INT | PA | PC | PU |
|---|---|---|---|---|---|---|---|
| **CI** | 0.658 | | | | | | |
| **C** | 0.465 | 0.724 | | | | | |
| **INT** | 0.713 | 0.800 | 0.667 | | | | |
| **PA** | 0.490 | 0.768 | 0.575 | 0.738 | | | |
| **PC** | 0.670 | 0.781 | 0.598 | 0.745 | 0.704 | | |
| **PU** | 0.615 | 0.751 | 0.707 | 0.717 | 0.636 | 0.650 | |
| **SA** | 0.409 | 0.627 | 0.911 | 0.625 | 0.609 | 0.514 | 0.617 |

4.2 Structural Model Results

Inner variance inflation factor values ranged from 1.295 to 2.088, below the threshold of 3, indicating no collinearity concerns among predictors (Table 3, Section 4.3) [12].

Following common PLS-SEM benchmarks [12], the explanatory power of the model varied across the endogenous constructs (Table 3). Satisfaction reached a moderate level (adjusted $R^2 = 0.554$), perceived usefulness approached a moderate level (adjusted $R^2 = 0.426$), and continuance intention showed weak-to-moderate explanatory power (adjusted $R^2 = 0.373$). These values are read against the aim of the analysis, which is to test theory-derived relationships among the constructs rather than to maximize explained variance [12]. The continuance-intention value is also close to the 41% reported in the original ECM study [4].

As shown in Table 3, the effect sizes for the individual paths showed that the largest effects involve post-adoption evaluations – confirmation on satisfaction ($f^2 = 0.746$) and perceived usefulness on continuance intention ($f^2 = 0.218$) – whereas the remaining effects were small, and those of perceived competence ($f^2 = 0.007$) and the usefulness – satisfaction path ($f^2 = 0.017$) fell below the benchmark for a small effect [12].

4.3 Hypothesis Testing

The hypothesis testing results (Table 3) showed that seven of the nine hypothesized direct effects were supported. The strongest direct effect was Confirmation to Satisfaction ($\beta = 0.686$, $p < 0.001$), indicating that students' satisfaction with Generative AI was closely associated with whether actual

experience meets or exceeds prior expectations. Perceived usefulness exerted a positive effect on satisfaction that met the significance criterion exactly at the threshold (β = 0.103, $p$ = 0.050); given its negligible effect size ($f^2$ = 0.017), H7 is supported in statistical terms but marginal in practical terms.

For continuance intention, Perceived Usefulness to Continuance Intention was supported (β = 0.419, $p$ < 0.001), making perceived usefulness the strongest direct predictor of continued use. Satisfaction to Continuance Intention was also significant (β = 0.293, $p$ < 0.001), but its coefficient was smaller.

Among the antecedents of perceived usefulness, confirmation had the largest effect (β = 0.288, $p$ = 0.001), followed by perceived anthropomorphism, perceived intelligence, and perceived autonomy (Table 3). Perceived Competence to Perceived Usefulness was not supported (β = 0.086, $p$ = 0.242), a result examined further in Section 4.5.

**Table 3** Structural model assessment and hypothesis testing results

| Endogenous construct $R^2$ (adj. $R^2$) | Hypothesis: path | Inner VIF | $f^2$ | β | $p$ | Note |
|---|---|---|---|---|---|---|
| **PU: 0.436 (0.426)** | H1: INT → PU | 2.088 | 0.025 | 0.172 | 0.036 | Supported |
| | H2: ANT → PU | 1.580 | 0.035 | 0.176 | 0.006 | Supported |
| | H3: PA → PU | 1.649 | 0.018 | 0.131 | 0.034 | Supported |
| | H4: PC → PU | 1.771 | 0.007 | 0.086 | 0.242 | Not supported |
| | H5: C → PU | 1.527 | 0.097 | 0.288 | 0.001 | Supported |
| **SA: 0.557 (0.554)** | H6: C → SA | 1.425 | 0.746 | 0.686 | < 0.001 | Supported |
| | H7: PU → SA | 1.425 | 0.017 | 0.103 | 0.050 | Marginally supported |
| **CI: 0.378 (0.373)** | H8: PU → CI | 1.295 | 0.218 | 0.419 | < 0.001 | Supported |
| | H9: SA → CI | 1.295 | 0.106 | 0.293 | < 0.001 | Supported |

*Note:* INT = perceived intelligence; ANT = perceived anthropomorphism; PA = perceived autonomy; PC = perceived competence; C = confirmation; PU = perceived usefulness; SA = satisfaction; CI = continuance intention.

Bootstrapping of the specific indirect effects on continuance intention indicated that five of the seven examined paths were statistically significant: Confirmation → Satisfaction → Continuance Intention (β = 0.201, $p$ < 0.001), Confirmation → Perceived Usefulness → Continuance Intention (β = 0.121, $p$ = 0.002), Perceived Anthropomorphism → Perceived Usefulness → Continuance Intention (β = 0.074, $p$ = 0.011), Perceived Intelligence → Perceived Usefulness → Continuance Intention (β = 0.072, $p$ = 0.048), and Perceived Usefulness → Satisfaction → Continuance Intention (β = 0.030, $p$ = 0.043); the corresponding paths from perceived autonomy (β = 0.055, $p$ = 0.059) and perceived competence (β = 0.036, $p$ = 0.255) were not significant.

4.4 Total Effects and Importance-Performance Map Analysis

Table 4 reported the total effects and the Importance-Performance Map Analysis (IPMA) [15]. Perceived usefulness recorded the strongest total effect on continuance intention (β = 0.449), followed by confirmation (β = 0.330) and satisfaction (β = 0.293), all significant at $p$ < 0.001. Perceived anthropomorphism (β = 0.079, $p$ = 0.010) and perceived intelligence (β = 0.077, $p$ = 0.047) had significant but smaller total effects, perceived autonomy showed a marginal total effect (β = 0.059, $p$ = 0.057), and perceived competence remained non-significant (β = 0.038, $p$ = 0.249). The IPMA identified perceived usefulness as the most important area for improving continuance intention, followed by confirmation and satisfaction. Because no construct fell into the high-importance, low-performance quadrant, the strategic priority is to sustain and incrementally enhance these three drivers rather than to correct an urgent performance gap.

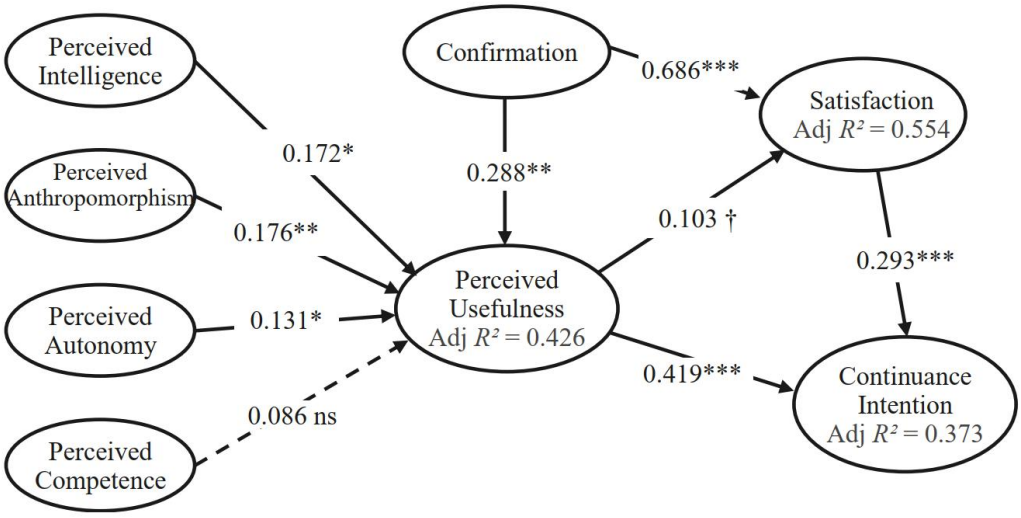



**Figure 1** Estimated structural model with standardized path coefficients and adjusted $R^2$

*Note:* *$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant; † $p = 0.050$, marginally supported (H7). Dashed path = not supported (H4). Values in endogenous constructs are adjusted $R^2$.

**Table 4** Total effects and Importance-Performance Map Analysis results

| Antecedent construct | Total effect | *p* | Performance |
|---|---|---|---|
| Perceived Usefulness | 0.449 | < 0.001 | 70.691 |
| Confirmation | 0.330 | < 0.001 | 68.901 |
| Satisfaction | 0.293 | < 0.001 | 68.019 |
| Perceived Anthropomorphism | 0.079 | 0.010 | 60.942 |
| Perceived Intelligence | 0.077 | 0.047 | 66.020 |
| Perceived Autonomy | 0.059 | 0.057 | 72.548 |
| Perceived Competence | 0.038 | 0.249 | 67.808 |

*Note: target construct: continuance intention.*

4.5 Discussion

The findings support the relevance of the ECM in explaining students' continued use of Generative AI. Consistent with recent research on Generative AI continuance in education [8], perceived usefulness and satisfaction were the main direct predictors of continuance intention, while confirmation was the principal antecedent of satisfaction and perceived usefulness.

Technology-specific characteristics influenced continuance intention primarily by strengthening perceived usefulness: systems perceived as capable of understanding requests and communicating in an accessible, human-like manner were regarded as more academically valuable. The perceived intelligence result is consistent with Moussawi et al. [6] but contrasts with Singh and Paiva [7], who found intelligence to predict ease of use instead; the significant anthropomorphism effect likewise contrasts with their non-significant post-adoption finding. These differences suggest that the influence of capability and human-likeness cues is context-dependent. Nevertheless, human-like fluency should not be interpreted as evidence of factual accuracy, and institutional training should help students distinguish accessible conversational support from unverified, biased, or misleading outputs.

From an SDT perspective [5], perceived autonomy was positively related to perceived usefulness, whereas perceived competence was not (H4). Two features of the study help account for this result. First, the competence indicators measure students' confidence in operating Generative AI for learning tasks rather than their ability to verify or critically appraise its outputs. Second, all respondents already had hands-on experience with these tools. Among experienced users, basic operating capability plausibly functions as a threshold condition: once students can formulate prompts and navigate the tools, additional confidence adds little to usefulness judgments, which rest instead on whether outputs are accurate, relevant, and applicable to coursework [4, 9]. Comparable results appear in recent studies: Tummalapenta et al. [10] also found no significant competence–usefulness relationship, with competence relating to ease of use instead, and Zhou and Zhang [11] linked competence primarily to intrinsic motivation and satisfaction rather than to usefulness. An additional possibility, consistent with the documented limitations of Generative AI [3], is that more capable users scrutinize outputs more closely and recognize hallucinated claims or fabricated references more readily, so that competence raises the standard against which usefulness is judged; testing this account would require measures of verification and critical-appraisal skills beyond the present scale. For practice, these results suggest that institutions strengthen task-specific verification and critical evaluation rather than rely on operating proficiency alone to raise perceived usefulness.

Overall, sustainable use requires balancing usefulness, satisfaction, and autonomy with responsible academic guidance, positioning the technology as a learning support system rather than a shortcut.

## 5 Conclusion and Recommendations

This study examined students' continuance intention to use Generative AI for academic purposes, extending the Expectation Confirmation Model with two psychological need perceptions and two technology-specific attributes. Based on 269 valid responses analyzed with PLS-SEM, seven direct effects were supported, with the usefulness–satisfaction path only marginal and the competence path non-significant. The model accounted for 37.3% of continuance-intention variance, and confirmation was the main upstream construct shaping both mediators.

Theoretically, the study showed that the ECM retained its explanatory core when augmented with SDT-informed need perceptions and technology-specific attributes. It also provided empirical evidence from a Vietnamese international higher education context, and indicated that Generative AI continuance was sustained less by novelty than by confirmed usefulness, satisfaction, and meaningful learning support.

For administrators, the results suggested the need for clear guidelines on responsible Generative AI use, including acceptable academic practices, output verification, citation, plagiarism prevention, and data privacy, together with practical training on prompt design, critical evaluation, and ethical decision-making. For lecturers, assignments should require students to compare generated responses with scholarly sources, document prompts, revise outputs, and explain how the technology contributed to their learning, thereby strengthening usefulness while reducing passive dependence.

The study has several limitations. It relies on a cross-sectional design, self-reported data, positive antecedents only, and a selective operationalization of SDT in which relatedness was not modeled. In addition, the model incorporates positive motivational antecedents only and does not yet integrate negative or inhibiting factors such as perceived risk, academic integrity concerns, or passive dependence and habit. Although the sample of 269 satisfies common minimum requirements for PLS-SEM, it is adequate rather than large for a model with eight constructs and 31 indicators, and the HTMT between confirmation and satisfaction (0.911) remains a measurement limitation that future scale refinement should address. The model explains 37.3% of

continuance intention, leaving approximately 62.7% of the variance outside the current framework. Generalizability is also constrained because respondents were recruited by convenience and referral sampling within one bilingual institute at a single private university, so the results describe this setting rather than Vietnamese higher education at large. Future research should employ longitudinal and multi-institutional designs with larger samples, extend the model with variables such as perceived risk, subjective norms, habit, trust calibration, and academic integrity concerns, refine the measurement of confirmation and satisfaction to sharpen their empirical distinctiveness, compare different Generative AI tools, and investigate relatedness in collaborative technology-supported learning.

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**Tóm tắt** Nghiên cứu này xem xét các yếu tố thúc đẩy sinh viên tiếp tục sử dụng trí tuệ nhân tạo tạo sinh (Generative AI) cho mục đích học thuật tại Viện Đào tạo Song ngữ, Trường Đại học Nguyễn Tất Thành. Nghiên cứu mở rộng Mô hình Xác nhận Kỳ vọng bằng hai nhận thức dựa trên Lý thuyết Tự quyết, gồm quyền tự chủ và năng lực, cùng hai đặc tính của Generative AI là trí thông minh cảm nhận và tính nhân hóa cảm nhận. Dữ liệu khảo sát từ 269 sinh viên đã có kinh nghiệm sử dụng Generative AI trong học tập được phân tích bằng PLS-SEM. Bảy mối quan hệ trực tiếp được ủng hộ; tác động của tính hữu ích đến sự hài lòng chỉ đạt mức sát ngưỡng, trong khi tác động của năng lực cảm nhận đến tính hữu ích không có ý nghĩa thống kê. Mô hình giải thích 37,3 % biến thiên của ý định tiếp tục sử dụng. Tính hữu ích cảm nhận là yếu tố dự báo trực tiếp mạnh nhất, tiếp theo là sự hài lòng. Kết quả góp phần mở rộng nghiên cứu về hành vi hậu chấp nhận trong bối cảnh giáo dục đại học quốc tế tại Việt Nam, đồng thời gợi ý các trường đại học cần nâng cao giá trị học thuật, sự hài lòng, quyền tự chủ của người học và việc sử dụng Generative AI có trách nhiệm.

**Từ khóa** Trí tuệ nhân tạo tạo sinh; ý định tiếp tục sử dụng; mô hình xác nhận kỳ vọng; lý thuyết tự quyết; giáo dục đại học.