Journal of Applied Data Sciences
Vol. 7, No. 2, May 2026, pp. 1349-1362

ISSN 2723-6471
1349

Cognitive and Technological Factors Shaping Students' Sustained Use of ChatGPT in Higher Education

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(Received: November 10, 2025; Revised: January 5, 2026; Accepted: March 12, 2026; Available online: April 26, 2026)

Abstract

This study examines the cognitive and technological factors shaping students' sustained use of ChatGPT in Indonesian higher education. Despite the rapid adoption of generative Artificial Intelligence (AI) in education, a clear understanding of the factors sustaining continued engagement with such systems remains limited. While continuance intention has been widely examined, the application of the Expectation–Confirmation Model (ECM) in generative AI contexts remains underexplored. This gap is especially evident when considering the role of AI-specific system attributes in shaping post-adoption evaluations. Although ECM has been extended with various constructs in prior studies, the specific integration of AI characteristics, particularly perceived intelligence and anthropomorphism, has not been explored in generative AI use in education, especially within Indonesian higher education. To address this gap, a multi-theoretic framework integrating ECM and AI characteristics was developed. Data from 322 Indonesian students were analyzed using Partial Least Squares-Structural Equation Modeling. All ten hypotheses were supported, and the model explains 43.3% of the variance in continuance intention ($R^2 = 0.433$). Perceived Intelligence strongly influences Perceived Anthropomorphism with a path coefficient of 0.591, representing the strongest relationship in the model, while other paths demonstrate moderate or modest effects. The findings confirm ECM's robustness in generative AI settings and highlight the pivotal role of AI characteristics in shaping post-adoption evaluations and sustained use. These results contribute to the growing body of research on generative AI adoption in education by demonstrating how system intelligence and human-like interaction jointly influence continuance intention. The findings also offer practical guidance for AI developers to enhance system intelligence and natural interaction. Future research could explore how students experience AI over time and what shapes their sustained use using different research methods.

Keywords: ChatGPT, Continuance Intention, Expectation-Confirmation Model, AI Characteristics, Perceived Intelligence, Perceived Anthropomorphism

1. Introduction

ChatGPT has been widely applied across multiple domains, including education [1]. A systematic review summarizes key issues related to the benefits, challenges, and ethics of ChatGPT in higher education [2]. ChatGPT is also used to enhance personalized learning by offering materials that match students' needs and comprehension levels [1], [3].

To optimize the implementation of ChatGPT in education, various studies have explored the factors influencing its effectiveness in supporting learning, providing additional resources, and facilitating academic tasks [4]. Given its significant potential in education and its ability to enhance learning processes, a comprehensive understanding of the factors affecting students' intention to use ChatGPT is a crucial area of study [5]. A research analyzing the factors influencing ChatGPT adoption and use has been conducted using the Technology Acceptance Model (TAM) and its extension [4], [5], and [6]. Although analyzing the initial use of an information system is an important first step in determining its success, recent studies [7] increasingly emphasize the importance of understanding whether users continue to rely on the system after the adoption stage, highlighting the growing relevance of continuance intention research.

Prior studies have investigated continuance intention of ChatGPT using various theoretical frameworks, including Information System Success Model (ISSM) and Stimulus-Organism-Response (S-O-R) [8], Unified Theory of Acceptance and Use of Technology (UTAUT) and S-O-R [9], and ECM (Expectation Confirmation Model) which has

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DOI: https://doi.org/10.47738/jads.v7i2.1291

proven to be a good model for explaining continuance intentions [10]. Moreover, ECM and AI characteristics are applied to investigate continuance intention in banking applications powered by artificial intelligence [11]. As a generative artificial intelligence, ChatGPT exhibits distinctive characteristics that are perceived by users during system interaction and use. These characteristics are primarily reflected in users' perceptions of the system's intelligence and its human-like qualities in delivering responses.

Perceived intelligence relates to ChatGPT's ability to understand context and provide relevant answers, while perceived human-likeness is reflected in a natural and easily comprehensible communication style. Despite these distinctive characteristics and the increasing adoption of ChatGPT in higher education, the factors that influence students' continuance use of this technology remain insufficiently understood. Previous studies have examined continuance intention in AI-based services using various theoretical perspectives. For instance, ECM and AI characteristics have been applied to investigate experienced Chinese users' continuance intention in mobile banking applications powered by artificial intelligence [11]. However, the integration of ECM and AI characteristics to explain the continuance use of ChatGPT in educational settings, particularly in Indonesian higher education, remains limited. This study conceptualizes the determinants of ChatGPT continuance use from two dimensions: cognitive factors and technological characteristics. Cognitive factors, grounded in the Expectation–Confirmation Model (ECM), refer to students' evaluative judgments, including confirmation, perceived usefulness, and satisfaction, which shape their post-adoption intentions. In contrast, technological factors capture users' perceptions of the AI system's attributes, specifically perceived intelligence and anthropomorphism, which represent key characteristics of generative AI systems. Based on this conceptualization, this study integrates constructs from the Expectation–Confirmation Model and AI-related characteristics to explain students' continuance intention to use ChatGPT. To support the generalizability of the findings, the study involves respondents from diverse backgrounds across Indonesia, ensuring broader representation within higher education.

2. Theoretical Backgrounds

2.1. ChatGPT

ChatGPT, a generative artificial intelligence (AI) chatbot developed by OpenAI, marks a significant advancement in natural language processing (NLP) and educational technology. It is built on the Generative Pre-trained Transformer (GPT) architecture and has evolved through successive iterations, where each improving contextual comprehension, coherence, and response generation [12], [13], [1]. Functionally, ChatGPT supports a wide array of tasks, including text generation, summarization, translation, question answering, and original content creation [2], [1].

In the context of higher education, ChatGPT has been widely adopted to support asynchronous learning, content creation, academic writing, personalized feedback, and formative assessment [3], [14]. It enhances instructional delivery by offering cognitive offloading for educators, while also enabling students to engage in hypothesis formulation, collaborative learning, and problem-solving [15], [3], [2].

Tasks such as assisting with academic writing, delivering personalized feedback, and supporting problem-solving [14], [15], [3], [2] reflect core capabilities of generative AI systems like ChatGPT, which communicate with users through natural language dialogue and contextually appropriate responses. Such interaction mechanisms may lead users to perceive the system as intelligent in generating contextually appropriate responses and human-like in its conversational interaction, thereby relating to the constructs of perceived intelligence and perceived anthropomorphism [16] examined in this study.

2.2. Expectation-Confirmation Model (ECM)

The ECM, introduced by Bhattacherjee [7], offers a theoretically grounded framework to explain users' continuance intention as the decision to persist in using an information system after initial adoption. The model consists of four core constructs: confirmation, perceived usefulness, satisfaction, and continuance intention. Confirmation (CON) refers to the degree of congruence between users' pre-adoption expectations and their actual experiences with the system where a higher degree of confirmation implies that the system has met or exceeded expectations. Perceived Usefulness (PU) represents the extent to which the system is believed to enhance users' performance, formed after usage rather than anticipated beforehand. Satisfaction (SAT) captures the affective response resulting from users' post-adoption evaluation of the system, reflecting their overall contentment. Continuance Intention (CUI) denotes the user's intention to continue engaging with the system over time. Bhattacherjee [7] empirically validated a series of causal relationships among these constructs: confirmation positively influences both perceived usefulness and satisfaction; perceived usefulness further enhances satisfaction; and both satisfaction and perceived usefulness directly determine continuance intention.

2.3. AI Characteristics

Although prior studies in human–AI interaction have identified multiple attributes, including animacy [16], empathy [17], reliability [18], and trustworthiness [18], not all are equally relevant in the context of generative AI. Perceived animacy is typically associated with embodied or visually represented agents [16], whereas systems such as ChatGPT operate primarily through text-based interaction. Empathy is less central, as user interactions are predominantly cognitive and task-oriented rather than emotional [17]. Reliability and trustworthiness, while important, are conceptually reflected in users' evaluation of system competence [18] and are therefore subsumed under perceived intelligence. Accordingly, this study focuses on perceived intelligence and perceived anthropomorphism [16] as theoretically grounded and parsimonious dimensions that capture both the functional and human-like aspects of AI interaction in generative AI environments. Perceived Anthropomorphism (PA) is defined as the degree to which users attribute humanlike characteristics, intentions, or behaviors to non-human agents [16]. In the context of ChatGPT, this perception primarily emerges from its natural conversational style, interactive responses, and human-like language expression rather than from physical or visual human features. Perceived Intelligence (PI) refers to users' perceptions of an AI system's capabilities [16]. Since the early development of intelligent systems in information systems, intelligence has been a defining characteristic that distinguishes AI from other technologies. Crucially, PI depends on users' belief in the system's competence.

3. Hypothesis Development

3.1.Perceived Intelligence (PI)

In [11], the intelligent capabilities of AI-based mobile banking applications support users in efficiently managing banking services, thereby increasing the perceived usefulness of the app. Intelligent features in AI apps can make users perceive them as more human-like, suggesting that AI intelligence may enhance perceived anthropomorphism [11]. When users perceive that the intelligence function of the apps meets their expectations regarding the services, their confirmations following the use of the apps are guaranteed [11]. Although [11] examine AI-enabled mobile banking applications originating from contexts outside education, the study primarily focuses on artificial intelligence systems that exhibit intelligent and anthropomorphic characteristics rather than on the specific application domain. It investigates AI-enabled mobile banking applications that understand user needs, provide personalized financial solutions, and communicate in a human-like manner. This study is therefore cited not for its application domain but for providing foundational evidence regarding theoretical relationships involving AI-specific characteristics. The core constructs, perceived intelligence and perceived anthropomorphism, are inherent characteristics of artificial intelligence systems and are not limited to any application domain. Consequently, theoretical relationships identified in these diverse AI contexts are conceptually transferable to educational settings involving generative AI systems such as ChatGPT. Across these contexts, users interact with AI agents that exhibit intelligent and human-like capabilities. This conceptual alignment supports the use of these citations, while the present study empirically examines these relationships in the Indonesian higher education context. Thus, we propose the following hypothesis:

H1: Perceived Intelligence positively influences Perceived Usefulness.

H2: Perceived Intelligence positively influences perceived anthropomorphism.

H3: Perceived intelligence positively influences confirmation.

3.2. Perceived Anthropomorphism (PA)

PA in mobile banking apps fosters the perception that the service is friendly and human-like, similar to interactions with real people. This perception encourages users to feel that the services meet their expectations. As a result, PA supports a consistent perception of alignment between users' expectations and the actual performance of the app [11]. Consequently, PA contributes to CON, the perception that actual system performance matches or exceeds initial expectations [29]. PA enhances PU by enabling apps to address problems more flexibly from a human-like perspective. Human-like communication from AI further strengthens users' sense of effective assistance [11]. This leads to the following hypothesis in the context of education as discussed in this paper:

H4: Perceived anthropomorphism positively influences confirmation.

H5: Perceived anthropomorphism positively influences perceived usefulness.

3.3. Perceived Usefulness (PU)

Within the educational context, PU reflects the extent to which students perceive ChatGPT as a helpful tool in enhancing the efficiency of their research activities [6], as well as improving their overall performance, productivity, and learning outcomes [19]. An investigation into the determinants of ChatGPT adoption among university students and its impact on learning satisfaction found that PU positively influenced learning satisfaction [6]. The study in [20] identifying factors influencing the continued use of ChatGPT in higher education shows that PU is one of the core factors affecting users' satisfaction. Given the theoretical rationale discussed above, it is reasonable to propose the following hypothesis:

H6: Perceived Usefulness positively influences Satisfaction.

While Davis established PU's critical role in shaping initial adoption intentions, Bhattacherjee [7] later empirically demonstrated that PU also directly influences users' continuance intention in the context of the ECM. The link between PU and CUI in educational settings has been examined in prior studies, including [20] and [21]. Drawing on the theoretical foundation discussed earlier, we hypothesize the following:

H7: Perceived Usefulness positively influences Intention to continue using ChatGPT

3.4.Confirmation (CON)

CON as part of Expectation-Confirmation model is discussed in [22] and [21]. The study to analyze behavioral intentions toward ChatGPT highlights that CON has a positive relationship with PU as well as SAT [23]. An empirical study on the continuance and recommendation intention of ChatGPT using an extended Technology Continuance Theory reports a positive relationship between CON and both PU and SAT [24]. Thus, the following hypothesis are posited:

H8: Confirmation positively influences Perceived Usefulness

H9: Confirmation positively influences Satisfaction

3.5. Satisfaction (SAT)

According to the ECM [7], SAT arises when the system meets or exceeds initial expectations. In the study which analyzes behavioral intentions toward ChatGPT, the study finds that SAT positively influences the CUI [23]. Across multiple higher education contexts, satisfaction has been consistently identified as a significant determinant of continuance intention in ChatGPT usage studies [8], [25], [24]. Drawing on the theoretical relationships outlined earlier, this study proposes the following hypothesis:

H10: Satisfaction positively influences intention to continue using ChatGPT.

3.6. Continuance Intention to Use (CUI)

Prior studies have investigated ChatGPT continuance intention in educational contexts using diverse theoretical approaches, such as TAM, ECM, ISSM, S-O-R, and other extended continuance frameworks [8], [9], [20], [23], [24], [25], [26].

4. Research Methodology

This study adopts a quantitative research methodology, specifically employing the PLS-SEM approach to analyze interactions between multiple constructs. Furthermore, [27] emphasize the importance of rigorous and transparent reporting when applying PLS-SEM. They highlight updated metrics such as PLS predict for assessing out-of-sample predictive power, alongside established evaluation criteria like composite reliability, average variance extracted (AVE), the Fornell-Larcker criterion, and the Heterotrait-Monotrait ratio (HTMT). In light of these advancements, this study integrates both established and contemporary best practices in the application and reporting of PLS-SEM, ensuring the methodological rigor and credibility of the structural model results. The overall research process is illustrated in figure 1.

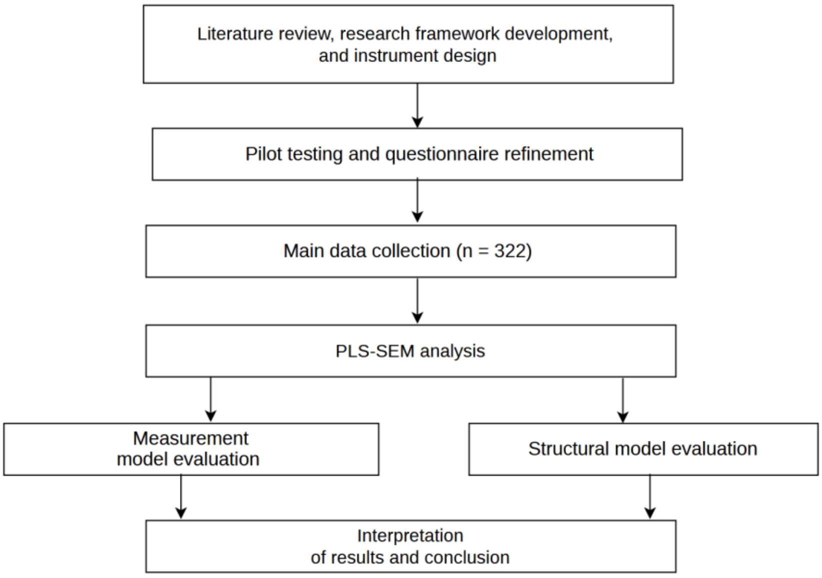

Figure 1. Research process flowchart

4.1. Instrument Development

Measurement items were initially adapted from prior studies, yielding eight to ten items per construct. These items were subsequently reduced to three to four through a content validity–oriented evaluation, focusing on conceptual relevance to construct definitions, redundancy elimination, and clarity of expression. Generative AI (ChatGPT) was used as a supporting tool by providing construct definitions alongside candidate items through structured prompts (e.g., requesting the system to assess item–construct alignment, identify redundant or conceptually weak items, and assist in prioritizing items based on conceptual fit). The process was conducted iteratively to refine and stabilize the outputs. To control potential bias, AI-generated suggestions were not directly adopted; instead, they were systematically compared against theoretical definitions and prior literature and only retained when conceptually justified. All final decisions were made by the authors, ensuring that AI assistance did not override theoretical judgment. A pilot test was subsequently conducted to confirm clarity and comprehensibility prior to full data collection. This approach is consistent with prior studies highlighting AI's role in enhancing research efficiency [28], [29]. A formal reliability and validity assessment, including Cronbach's alpha and outer loadings, is subsequently conducted. The following table 1 summarizes the final measurement items that were administered to respondents across all constructs.

Table 1. Measurement Items

Constructs	Items	Adapted from
PI	PI1 – ChatGPT can communicate with me in a way that I understand.	[11], [30], [31]
	PI2 – ChatGPT can provide me with a useful answer that helps my learning comprehension.	[31]
	PI3 – ChatGPT can find and process the necessary information to assist me in learning.	[30], [31]
PA	PA1 – ChatGPT feels friendly during interactions.	[11], [31], [30]
	PA2 – ChatGPT makes me feel appreciated.	[11], [31], [30]
	PA3 – ChatGPT adapts its responses to match the user's communication style, making interactions feel more natural.	[16], [11], [31], [30]
PU	PU1 – The support provided by ChatGPT meets my learning needs.	[11]
	PU2 – The various features offered by ChatGPT are useful for my learning process.	[32], [11], [10]
	PU3 – Using ChatGPT increases my productivity in learning.	[10], [32]

SAT	SAT1 – Overall, I am satisfied with the learning experience facilitated by ChatGPT in my studies.	[11], [6]
	SAT2 – I think the experience of using ChatGPT for learning is pleasant.	[11], [10]
	SAT3 – I am highly satisfied with the accuracy and relevance of ChatGPT's responses in my learning process.	[22], [11], [6]
CON	CON1 – My experience using ChatGPT for learning was better than I expected.	[10], [22]
	CON2 – The responses provided by ChatGPT were better than I expected.	[11], [10], [22]
	CON3 – I feel that the benefits of using ChatGPT for learning are greater than what I expected.	[11]
CUI	CUI1 – I intend to continue using ChatGPT in my learning process and not stop using it.	[10], [11], [22]
	CUI2 – I intend to continue using ChatGPT as a learning aid rather than switching to other learning aids.	[22], [10]
	CUI3 – I will use ChatGPT on a regular basis in my future learning activities.	[22]

4.2. Research Framework

Grounded in prior research, this study proposes a research framework as depicted in figure 2.

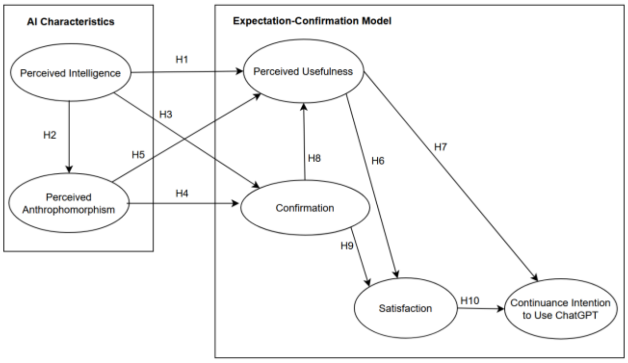

Figure 2. Proposed Research Framework

The proposed framework integrates AI-specific characteristics with the Expectation Confirmation Model (ECM) to explain continuance intention in the context of generative AI. Perceived intelligence is positioned as a key antecedent because users' evaluation of the system's capability can shape their perceptions of usefulness, confirmation of expectations, and anthropomorphic interpretations. Perceived anthropomorphism is expected to influence confirmation and perceived usefulness, as human-like interaction may strengthen users' perceived alignment with the system and enhance its perceived effectiveness. The relationships among confirmation, perceived usefulness, satisfaction, and continuance intention follow the established logic of ECM, which explains how post-adoption evaluations drive sustained usage. By integrating these mechanisms with AI-specific perceptions, the framework captures both general post-adoption processes and characteristics unique to generative AI systems such as ChatGPT. Overall, the framework consists of six constructs and ten hypotheses, reflecting a comprehensive approach to understanding sustained use of AI-based learning tools in the Indonesian higher education context.

4.3. Data Collection and Analysis

This study utilizes a questionnaire based on a 7-point Likert scale, where responses range from 1 (Strongly Disagree) to 7 (Strongly Agree), to assess the six research variables. The data collection was conducted through questionnaire distribution from March to October 2025. Respondents were sourced through a combination of personal academic networks, PopSurvey by Populix as one of Indonesia's largest survey platforms, and additional public recruitment channels. The study specifically targeted university students. To ensure that respondents belonged to the intended population, participants were required to confirm their status as university students and indicate their current semester of study. In addition, the survey introduction explicitly stated that the study focused on the use of ChatGPT in higher education, and participation was voluntary. This context encouraged participation primarily from students who were familiar with or had experience using ChatGPT in their academic activities. The proposed hypotheses were analyzed using PLS-SEM with SmartPLS v4.1.0.9. The measurement model was evaluated using average variance extracted (AVE) and composite reliability (CR), computed as:

$$\mathrm{AVE} = \frac{1}{K}\sum_{k=1}^{K}\lambda_k^2, \quad \mathrm{CR} = \frac{(\sum_{k=1}^{K}\lambda_k)^2}{(\sum_{k=1}^{K}\lambda_k)^2 + \sum_{k=1}^{K}(1-\lambda_k^2)} \tag{1}$$

$\boldsymbol{\lambda_k}$ is the factor loading of indicator **k** and **K** the number of indicators.

The analysis followed a stepwise procedure, beginning with the measurement model assessment: reliability (Cronbach's α, CR) and convergent validity (AVE, factor loadings). This was followed by the discriminant validity assessment using HTMT and Fornell–Larcker criterion. Subsequently, the structural model evaluation was conducted in terms of collinearity (VIF), path coefficients (β), and explanatory power (R^2). Finally, bootstrapping with 5000 resamples was performed to determine the significance of path coefficients.

5. Results and Discussion

5.1. Demographics data analysis

Table 2 presents the demographic characteristics of the respondents. Based on the collected data, most respondents are female (72.67%) and primarily belong to Generation Z (98.45%). The largest proportion consists of final-year students (36.03%), suggesting substantial academic experience among participants. In terms of ethnicity, Javanese respondents dominate the sample (49.07%), reflecting the prominence of the group within Indonesia's diverse cultural landscape.

Table 2. Information of Participants

Item	Characteristics	Count	%
Gender	Male	88	27.33
	Female	234	72.67
Generation	Z	317	98.45
	Alpha	1	0.31
	Y	4	1.24
Year of Study	First Year	58	18.01
	Second Year	78	24.22
	Third Year	70	21.74
	Final Year	116	36.03
Ethnicity	Minangkabau	26	8.08
	Batak	22	6.83
	Javanese	158	49.07
	Chinese	24	7.45
	Sundanese	35	10.87
	Betawi	18	5.59
	Others	39	12.11

5.2. Measurement Model Evaluation

A total of 322 respondents completed the survey. Data analysis in this paper is performed according to [33], [27], [34], [35]. The measurement model is evaluated to ensure that all constructs are measured accurately and consistently. Four key indicators are examined: factor loadings (LF), Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE). As presented in table 3, the reliability of the constructs is confirmed as both Cronbach's Alpha and Composite Reliability values exceed 0.7, while convergent validity is established through factor loadings above 0.7 and AVE values greater than 0.5.

Table 3. Measurement Model Evaluation

Construct	Items	LF	CA	CR	AVE
PI	PI1	0.820	0.735	0.850	0.654
	PI2	0.823			
	PI3	0.782			
PA	PA1	0.810	0.723	0.845	0.646
	PA2	0.857			

	PA3	0.739			
PU	PU1	0.831	0.772	0.868	0.687
	PU2	0.832			
	PU3	0.823			
CON	CON1	0.872	0.849	0.908	0.768
	CON2	0.889			
	CON3	0.868			
SAT	SAT1	0.842	0.774	0.869	0.689
	SAT2	0.859			
	SAT3	0.787			
CUI	CUI1	0.891	0.877	0.924	0.802
	CUI2	0.874			
	CUI3	0.921			

5.3. Discriminant Validity Analysis

This study employed two complementary methods to assess discriminant validity: the Heterotrait–Monotrait (HTMT) ratio and the Fornell–Larcker criterion [27]. Table 4 presents the HTMT ratios for all construct pairs, which range from 0.547 to 0.870. Most values fall below the conservative threshold of 0.85, and all are within the acceptable range under the liberal criterion of 0.90, indicating that the constructs are sufficiently distinct [27], [35]. Only the SAT and PI pair exhibit relatively higher HTMT ratios 0.870. However, this value is theoretically reasonable, as it represents conceptually and behaviorally related dimensions. Although this slightly exceeds the conservative threshold of 0.85, it remains within the acceptable threshold of 0.90 [35]. Perceived intelligence reflects users' evaluation of the system's capability to generate relevant and meaningful responses, which directly contributes to their overall satisfaction. Therefore, a strong association between these constructs is expected in AI-based systems. The elevated HTMT value thus reflects their conceptual proximity rather than a lack of discriminant validity. Accordingly, the HTMT analysis provides strong and consistent evidence of satisfactory discriminant validity across all constructs.

Table 4. Discriminant Validity

Construct	HTMT						Fornell Larcker					
	CON	CUI	PA	PI	PU	SAT	CON	CUI	PA	PI	PU	SAT
CON							0.876					
CUI	0.745						0.645	0.895				
PA	0.737	0.663					0.578	0.531	0.804			
PI	0.729	0.547	0.806				0.575	0.439	0.591	0.809		
PU	0.706	0.734	0.771	0.798			0.574	0.608	0.575	0.603	0.829	
SAT	0.833	0.710	0.754	0.870	0.842		0.676	0.588	0.565	0.656	0.656	0.830

Table 4 also presents the Fornell–Larcker criterion values for all construct pairs. The diagonal elements represent the square root of the AVE for each construct, while the off-diagonal elements represent the inter-construct correlations. In all cases, the diagonal elements are greater than the corresponding off-diagonal elements, demonstrating satisfactory discriminant validity according to the Fornell–Larcker criterion. This indicates that each construct shares more variance with its own indicators than with those of any other construct, confirming that all constructs in the model are empirically distinct and conceptually independent [36]. Taken together, the HTMT and Fornell–Larcker results consistently support the discriminant validity of the constructs in this study.

5.4. Structural Model Evaluation

As part of the structural model evaluation, collinearity among the predictor constructs is examined using the Variance Inflation Factor (VIF). As presented in table 5, all VIF values are below the recommended threshold of 3.3, indicating the absence of multicollinearity as suggested in [27].

Table 5. Variance Inflation Factor (VIF) Values

Predictor → Endogenous	VIF
CON → PU	1.719
CON → SAT	1.491
PA → CON	1.536
PA → PU	1.767
PI → CON	1.536
PI → PA	1.000
PI → PU	1.757
PU → CUI	1.755
PU → SAT	1.491
SAT → CUI	1.755

Table 6 presents the R^2 and Adjusted R^2 values for all endogenous constructs in the model. According to [27], R^2 values of 0.75, 0.50, and 0.25 indicate substantial, moderate, and weak explanatory power, respectively. The results show that all endogenous constructs in this study exhibit moderate explanatory power, with all R^2 values exceeding the minimum threshold of 0.25. Specifically, the construct SAT demonstrates the highest explanatory power, with an R^2 value of 0.564 and the construct PA records the lowest R^2 value of 0.349, yet still above the weak threshold (0.25), suggesting that the model moderately explains the variability of this construct. The Adjusted R^2 values, which account for model complexity, are slightly lower than the R^2 values but remain consistent across constructs, confirming the model's robustness.

Table 6. R^2 and Adjusted R^2 of the Endogenous Constructs

Items	R-square	R-square adjusted
CON	0.418	0.415
CUI	0.433	0.429
PA	0.349	0.347
PU	0.474	0.470
SAT	0.564	0.561

5.5. Hypotheses Testing

To facilitate a more systematic and transparent interpretation of the structural model results, the magnitude of path coefficients is interpreted based on commonly adopted conventions in prior research [37]. Although strict cut-off values are not universally prescribed in PLS-SEM, path coefficients ranging from 0 to 0.10 are interpreted as weak, values between 0.11 and 0.30 as modest, values between 0.30 and 0.50 as moderate, and values above 0.50 as strong effects. Figure 3 presents the structural model with standardized path coefficients (β), significance levels, and R^2 values.

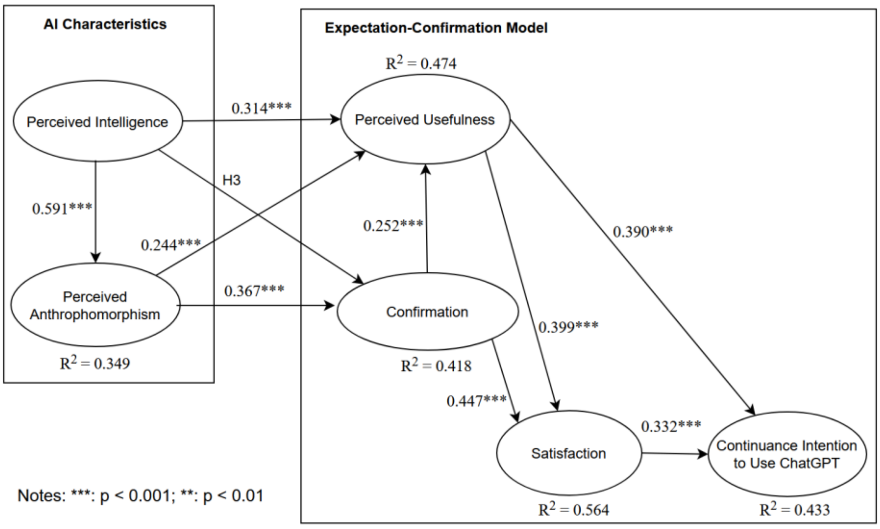

Figure 3. Structural model with standardized path coefficients (β), significance levels, and R^2 values

As shown in table 7, according to [37], the strongest path is observed between PI and PA (β = 0.591), indicating a robust association between users' perception of ChatGPT's intelligence and the extent to which it appears human-like. Several relationships exhibit moderate effect sizes, including CON → SAT, PA → CON, PI → CON, PI → PU, PU → CUI, PU → SAT, and SAT → CUI. The remaining paths show modest effects, suggesting that while their direct impacts are limited, they contribute complementary roles that enhance the coherence and interpretive depth of the overall model. From table 7, all hypothesized relationships are statistically significant, as indicated by t-values exceeding the critical thresholds ($t > 1.96$, $p \leq 0.05$; $t > 2.58$, $p \leq 0.01$; $t > 3.29$, $p \leq 0.001$), confirming the robustness and stability of the proposed structural model. Accordingly, all hypotheses are supported.

Table 7. Path Coefficients and Hypothesis Testing

Path	Path Coefficient	t-value	p-value	Decision
CON→ PU	0.252	4.253	0.000	Accepted
CON→ SAT	0.447	9.091	0.000	Accepted
PA → CON	0.367	6.257	0.000	Accepted
PA→ PU	0.244	3.547	0.000	Accepted
PI→ CON	0.359	6.366	0.000	Accepted
PI → PA	0.591	13.544	0.000	Accepted
PI→ PU	0.314	5.169	0.000	Accepted
PU→ CUI	0.390	7.321	0.000	Accepted
PU→ SAT	0.399	7.284	0.000	Accepted
SAT → CUI	0.332	6.013	0.000	Accepted

6. Discussion

This study successfully integrates an innovative multi-theoretical framework to explain the continuance intention of using ChatGPT among Indonesian university students from diverse cultural backgrounds. The framework incorporates AI Characteristics [11], [16], [30] and the ECM [7], [21], [38]. The results reveal several key findings that highlight the dominant role of AI characteristics and cognitive evaluations in shaping students' continuance intention to use ChatGPT. Notably, the strongest relationship in the model was observed between perceived intelligence and perceived anthropomorphism (β = 0.591), indicating that students' perception of ChatGPT's intelligence strongly shapes its perceived human-like qualities. When ChatGPT generates coherent and contextually appropriate responses, users tend to perceive the system as intelligent, commonly referred to as perceived intelligence [16], [11]. Conversely, when the responses are inaccurate or do not align with the context, users may question the system's capability, which in turn reduces their perception of its intelligence. This perception encourages users to interpret the system's responses as if they were produced by a human and to believe that the system is capable of understanding and thinking in a human-like manner, leading to stronger perceptions of anthropomorphism [16], [17]. As a result, users are more likely to perceive the system as human-like and associate it with human-like attributes.

The findings reveal that AI characteristics, namely perceived intelligence and perceived anthropomorphism, exert a positive influence on perceived usefulness and confirmation. These results are consistent with prior studies [11], which highlight that the intelligence and human-like attributes of AI are critical drivers in fostering users' belief in the system's benefits and in meeting their expectations when engaging with AI-based tools. The findings underscore the central role of the ECM as a core psychological mechanism. Specifically, expectation confirmation was found to be a primary driver of user satisfaction [11]. Meanwhile, perceived usefulness played a dual role: it directly reinforced satisfaction while also serving as a direct antecedent of continuance intention [38]. Consequently, both satisfaction and perceived usefulness emerged as the key determinants sustaining the intention to use ChatGPT [39]. These results reaffirm the relevance of ECM for explaining continuance behavior in the context of AI-based technologies and align with its well-established predictive power in non-AI information systems [40], [22], [21], [10].

For AI developers, the findings highlight the importance of enhancing systems such as ChatGPT to respond intelligently , interact naturally with users [17], adapt to diverse learning contexts, and exhibit human-like qualities and conversational fluidity [11], [16]. Equally important, the system should demonstrate clear educational usefulness [6], [19], [20], [41] by effectively supporting students' learning experiences. This ensures that users perceive ChatGPT as genuinely helpful rather than misleading due to hallucinations [42] thereby strengthening their motivation to continue using it.

7. Conclusions

This study contributes to the emerging body of research on generative AI use in Indonesian higher education by integrating technological and cognitive dimensions into a unified framework to explain students' continuance intention to use ChatGPT. By combining AI Characteristics with the Expectation–Confirmation Model (ECM), the proposed framework extends ECM to explain post-adoption behavior in generative AI–supported learning environments while demonstrating both theoretical robustness and contextual relevance. The findings provide recommendations for AI developers and educators to enhance system intelligence and human-like interaction, thereby strengthening expectation confirmation, perceived usefulness, and user satisfaction, which ultimately foster sustained continuance intention in higher education contexts.

The PLS-SEM results, based on data from 322 ethnically diverse respondents across Indonesia, demonstrate satisfactory reliability, validity, and predictive accuracy across all measurement and structural assessments. All ten hypotheses are supported, confirming the robustness of the proposed model. The analysis reveals that PI strongly drives PA, constituting the most dominant relationship in the model. Other paths yield moderate effects, the influence of PI on PU, and the effect of PU on SAT.

Despite its contributions, this study has several limitations that should be acknowledged. First, the data were collected using self-reported questionnaires, which may introduce potential response biases. Second, the cross-sectional design captures participants' perceptions at a single point in time and therefore limits the ability to examine how continuance intention and related perceptions evolve over time. Third, because all variables were measured using a single survey instrument, the possibility of common method bias cannot be entirely ruled out, although statistical checks indicated no severe issue. One limitation of this study also relates to the gender distribution of the respondents. The sample consists of a higher proportion of female participants (72.67%), which may influence the generalizability of the findings across different gender groups. Future studies may consider adopting a more balanced gender composition, for example by applying quota-based sampling or targeted recruitment strategies to ensure more proportional representation between male and female respondents. To obtain a deeper understanding of cognitive and technological factors influencing continuance usage intention, future research could adopt mixed-method designs [43] that integrate quantitative surveys with qualitative approaches such as interviews or focus groups. Alternatively, qualitative-only studies [44] may offer rich experiential insights into learners' usage experiences and how these experiences shape their perceptions, satisfaction, and continued use of AI tools. In addition, future research is encouraged to employ longitudinal designs to examine how key cognitive and technological determinants evolve over time and influence sustained continuance intention as prior studies have been conducted across various contexts, including education [45] and [32].

8. Declarations

8.1. Author Contributions

Conceptualization: A.A.; Methodology: A.A., A.E.W.; Software: A.A., H.; Validation: A.A., A.E.W.; Formal Analysis: A.A.; Investigation: A.A.; Resources: A.A., H.; Data Curation: A.A., A.E.W.; Writing Original Draft Preparation: A.A.; Writing Review and Editing: A.A., H, A.E.W.; Visualization: A.A.; All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.3. Funding

The authors received financial support for the research, authorship, and/or publication of this article from LPPM Universitas Pelita Harapan under research number of P-091-FTI/XII/2024.

8.4. Institutional Review Board Statement

Not applicable.

8.5. Informed Consent Statement

Not applicable.

8.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] P. P. Ray, "ChatGPT: a comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope," *Internet Things Cyber-Phys. Syst.*, vol. 3, no. Apr., pp. 121–154, 2023, doi: 10.1016/j.iotcps.2023.04.003.

[2] I. M. García-López, C. S. González González, M. S. Ramírez-Montoya, and J. M. Molina-Espinosa, "Challenges of implementing ChatGPT on education: systematic literature review," *Int. J. Educ. Res. Open,* vol. 8, no. Oct., pp. 1–12, 2025, doi: 10.1016/j.ijedro.2024.100401.

[3] B. Memarian and T. Doleck, "ChatGPT in education: methods, potentials, and limitations," *Comput. Hum. Behav. Artif. Humans*, vol. 1, no. Jun., pp. 1–12, 2023, doi: 10.1016/j.chbah.2023.100022.

[4] H. Albayati, "Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: a user acceptance perspective study," *Comput. Educ. Artif. Intell.*, vol. 6, no. Jan., pp. 1–12, 2024, doi: 10.1016/j.caeai.2024.100203.

[5] R. A. M. Abdalla, "Examining awareness, social influence, and perceived enjoyment in the TAM framework as determinants of ChatGPT: personalization as a moderator," *J. Open Innov. Technol. Mark. Complex.*, vol. 10, no. Sep., pp. 1–12, 2024, doi: 10.1016/j.joitmc.2024.100327.

[6] M. A. Almulla, "Investigating influencing factors of learning satisfaction in AI ChatGPT for research: university students perspective," *Heliyon,* vol. 10, no. Jun., pp. 1–12, 2024, doi: 10.1016/j.heliyon.2024.e32220.

[7] A. Bhattacherjee, "Understanding information systems continuance: an expectation-confirmation model," MIS Q., vol. 25, no. Sep., pp. 351–370, 2001, doi: 10.2307/3250921.

[8] C. D. Duong, T. H. Nguyen, T. V. N. Ngo, V. T. Dao, N. D. Do, and T. Van Pham, “Exploring higher education students’ continuance usage intention of ChatGPT: amalgamation of the information system success model and the stimulus-organism-response paradigm,” *Int. J. Inf. Learn. Technol.*, vol. 2024, no. Jan., pp. 1–12, 2024, doi: 10.1108/IJILT-01-2024-0006.

[9] C. D. Duong, “Modeling the determinants of HEI students’ continuance intention to use ChatGPT for learning: a stimulus–organism–response approach,” *J. Res. Innov. Teach. Learn.*, vol. 17, no. May, pp. 391–407, 2024, doi: 10.1108/JRIT-01-2024-0006.

[10] F. B. Franque, T. Oliveira, and C. Tam, “Understanding the factors of mobile payment continuance intention: empirical test in an African context,” *Heliyon,* vol. 7, no. Aug., pp. 1–12, 2021, doi: 10.1016/j.heliyon.2021.e07807.

[11] J. C. Lee, Y. Tang, and S. Q. Jiang, “Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model,” *Humanit. Soc. Sci. Commun.,* vol. 10, no. Jun., pp. 1–12, 2023, doi: 10.1057/s41599-023-01845-1.

[12] S. S. Gill and R. Kaur, “ChatGPT: vision and challenges,” *Internet Things Cyber-Phys. Syst*., vol. 3, no. May, pp. 262–271, 2023, doi: 10.1016/j.iotcps.2023.05.004.

[13] A. Zeb, R. Ullah, and R. Karim, “Exploring the role of ChatGPT in higher education: opportunities, challenges and ethical considerations,” *Int. J. Inf. Learn. Technol.,* vol. 41, no. Jan., pp. 99–111, 2024, doi: 10.1108/IJILT-04-2023-0046.

[14] M. I. Baig and E. Yadegaridehkordi, “ChatGPT in higher education: a systematic literature review and research challenges,” *Int. J. Educ. Res.*, vol. 127, no. Jul., pp. 1–12, 2024, doi: 10.1016/j.ijer.2024.102411.

[15] M. Javaid, A. Haleem, R. P. Singh, S. Khan, and I. H. Khan, “Unlocking the opportunities through ChatGPT tool towards ameliorating the education system,” *BenchCouncil Trans. Benchmarks Stand. Eval.,* vol. 3, no. Jun., pp. 1–12, 2023, doi: 10.1016/j.tbench.2023.100115.

[16] J. Balakrishnan and Y. K. Dwivedi, “Conversational commerce: entering the next stage of AI-powered digital assistants,” *Ann. Oper. Res.,* vol. 333, no. Feb., pp. 653–687, 2024, doi: 10.1007/s10479-021-04049-5.

[17] C. Pelau, D. C. Dabija, and I. Ene, “What makes an AI device human-like? the role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry,” *Comput. Hum. Behav.*, vol. 122, no. Sep., pp. 1–12, 2021, doi: 10.1016/j.chb.2021.106855.

[18] S. Wang, N. Fatima, M. Shahbaz, and M. Asif, “Building user trust in AI chatbots for customer service through human-like cues and perceived reliability,” *Sci. Rep*., vol. 16, no. Jan., pp. 1–14, 2026, doi: 10.1038/s41598-026-38179-2.

[19] A. S. Almogren, W. M. Al-Rahmi, and N. A. Dahri, “Exploring factors influencing the acceptance of ChatGPT in higher education: a smart education perspective,” *Heliyon,* vol. 10, no. Nov., pp. 1–12, 2024, doi: 10.1016/j.heliyon.2024.e31887.

[20] C. Yu, J. Yan, and N. Cai, “ChatGPT in higher education: factors influencing ChatGPT user satisfaction and continued use intention,” *Front. Educ*., vol. 9, no. May, pp. 1–11, 2024, doi: 10.3389/feduc.2024.1354929.

[21] S. H. Alshammari and R. A. Alshammari, “An integration of expectation confirmation model and information systems success model to explore the factors affecting the continuous intention to utilise virtual classrooms,” *Sci. Rep.,* vol. 14, no. Dec., pp. 1–12, 2024, doi: 10.1038/s41598-024-69401-8.

[22] R. Pereira and C. Tam, “Impact of enjoyment on the usage continuance intention of video-on-demand services,” *Inf. Manage.*, vol. 58, no. Oct., pp. 1–12, 2021, doi: 10.1016/j.im.2021.103501.

[23] D. Nan, S. Sun, S. Zhang, X. Zhao, and J. H. Kim, “Analyzing behavioral intentions toward generative artificial intelligence: the case of ChatGPT,” *Univers. Access Inf. Soc.,* vol. 24, no. Mar., pp. 885–895, 2025, doi: 10.1007/s10209-024-01116-z.

[24] R. S. Pasupuleti and D. Thiyyagura, “An empirical evidence on the continuance and recommendation intention of ChatGPT among higher education students in India: an extended technology continuance theory,” *Educ. Inf. Technol.,* vol. 29, no. Oct., pp. 17965–17985, 2024, doi: 10.1007/s10639-024-12573-7.

[25] C. N. L. Tan, M. Tee, and K. Y. Koay, “Discovering students’ continuous intentions to use ChatGPT in higher education: a tale of two theories,” *Asian Educ. Dev. Stud.,* vol. 13, no. Aug., pp. 356–372, 2024, doi: 10.1108/AEDS-04-2024-0096.

[26] S. R. Tummalapenta, R. S. Pasupuleti, R. M. Chebolu, T. V. Banala, and D. Thiyyagura, “Factors driving ChatGPT continuance intention among higher education students: integrating motivation, social dynamics, and technology adoption,” *J. Comput. Educ.,* vol. 2024, no. Dec., pp. 1–12, 2024, doi: 10.1007/s40692-024-00343-w.

[27] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. Jan., pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[28] J. P. Andersen, "Generative artificial intelligence (GenAI) in the research process – a survey of researchers' practices and perceptions," *Technol. Soc.,* vol. 81, no. Jun., pp. 1–12, 2025, doi: 10.1016/j.techsoc.2025.102813.

[29] M. Khalifa and M. Albadawy, "Using artificial intelligence in academic writing and research: an essential productivity tool," *Comput. Methods Programs Biomed. Update*, vol. 2024, no. Jan., pp. 1–12, 2024, doi: 10.1016/j.cmpbup.2024.100145.

[30] S. Moussawi, M. Koufaris, and R. Benbunan-Fich, "How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents," *Electron. Mark.*, vol. 31, no. Jun., pp. 343–364, 2021, doi: 10.1007/s12525-020-00411-w.

[31] S. Moussawi and M. Koufaris, "Perceived intelligence and perceived anthropomorphism of personal intelligent agents: scale development and validation," *IEEE Access,* vol. 2019, no. Jan., pp. 115–124, 2019, doi: 10.24251/HICSS.2019.015.

[32] V. Venkatesh and F. D. Davis, "Theoretical extension of the technology acceptance model: four longitudinal field studies," *Manage. Sci.*, vol. 46, no. Feb., pp. 186–204, 2000, doi: 10.1287/mnsc.46.2.186.11926.

[33] J. F. Hair, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, "Partial least squares structural equation modeling (PLS-SEM): an emerging tool in business research," *Eur. Bus. Rev.*, vol. 26, no. Mar., pp. 106–121, 2014, doi: 10.1108/EBR-10-2013-0128.

[34] J. Hair, C. L. Hollingsworth, A. B. Randolph, and A. Y. L. Chong, "An updated and expanded assessment of PLS-SEM in information systems research," *Ind. Manag. Data Syst*., vol. 117, no. Apr., pp. 442–458, 2017, doi: 10.1108/IMDS-04-2016-0130.

[35] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci*., vol. 43, no. Jan., pp. 115–135, 2015, doi: 10.1007/s11747-014-0403-8.

[36] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Mark. Res.,* vol. 18, no. Feb., pp. 39–50, 1981, doi: 10.2307/3151312.

[37] J. Hair and A. Alamer, "Partial least squares structural equation modeling (PLS-SEM) in second language and education research: guidelines using an applied example," *Res. Methods Appl. Linguist.*, vol. 1, no. Dec., pp. 1–12, 2022, doi: 10.1016/j.rmal.2022.100027.

[38] T. Hariguna, A. Ruangkanjanases, B. Bin Madon, and K. M. Alfawaz, "Assessing determinants of continuance intention toward cryptocurrency usage: extending expectation confirmation model with technology readiness," *SAGE Ope*n, vol. 13, no. Jan., pp. 1–12, 2023, doi: 10.1177/21582440231160439.

[39] D. T. Sasongko, P. W. Handayani, and R. Satria, "Analysis of factors affecting continuance use intention of the electronic money application in Indonesia," *Procedia Comput. Sci.*, vol. 197, no. Dec., pp. 42–50, 2021, doi: 10.1016/j.procs.2021.12.116.

[40] X. Yu, Y. Yang, and S. Li, "Users' continuance intention towards an AI painting application: an extended expectation confirmation model," *PLoS One,* vol. 19, no. May, pp. 1–12, 2024, doi: 10.1371/journal.pone.0301821.

[41] M. A. Bhuiyan, M. K. Rahman, V. Basile, H. Ping, and A. B. M. Mainul Bari, "Adoption of ChatGPT for students' learning effectiveness," *Int. J. Manag. Educ.*, vol. 23, no. Dec., pp. 1–12, 2025, doi: 10.1016/j.ijme.2025.101255.

[42] M. Chelli, "Hallucination rates and reference accuracy of ChatGPT and Bard for systematic reviews: comparative analysis," *J. Med. Internet Res.*, vol. 26, no. Jan., pp. 1–12, 2024, doi: 10.2196/53164.

[43] Q. Ma, P. Crosthwaite, D. Sun, and D. Zou, "Exploring ChatGPT literacy in language education: a global perspective and comprehensive approach," *Comput. Educ. Artif. Intell.*, vol. 7, no. Dec., pp. 1–12, 2024, doi: 10.1016/j.caeai.2024.100278.

[44] C. Wang, "Exploring medical students' intention to use of ChatGPT from a programming course: a grounded theory study in China," *BMC Med. Educ.,* vol. 25, no. Dec., pp. 1–12, 2025, doi: 10.1186/s12909-025-06807-6.

[45] A. Cvetkovic, I. Savolainen, M. Koike, and A. Oksanen, "A four-wave longitudinal study on attitudes toward the use of AI in different domains—The self-determination theory and locus of control perspective," *Telemat. Inform. Rep.*, vol. 18, no. Jun., pp. 1–12, 2025, doi: 10.1016/j.teler.2025.100220.