

**Determinants of Continuance Intention Toward
Generative AI for Learning and Skill
Development: The Mediating Roles of Perceived
Learning Effectiveness and Trust in AI**

Determinants of Continuance Intention Toward Generative AI for Learning and Skill Development: The Mediating Roles of Perceived Learning Effectiveness and Trust in AI

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LETTER OF TRANSMITTAL

22 July 2026

Mr. Ahmed Imran Kabir

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Subject: Submission of Project Report on “Determinants of Continuance Intention Toward Generative AI for Learning and Skill Development: The Mediating Roles of Perceived Learning Effectiveness and Trust in AI”

Dear Sir,

It is my great pleasure to present the undergraduate thesis titled as “Determinants of Continuance Intention Toward Generative AI for Learning and Skill Development: The Mediating Roles of Perceived Learning Effectiveness and Trust in AI” for the partial fulfilment of requirement of the degree of Bachelor of Business Administration (BBA), majoring in Business Analytics from the School of Business and Economics, United International University.

This study aims to evaluate the factors affecting learners' continuance intention for using generative artificial intelligence (GenAI) for learning and skill development. I have tried to perform the research study with sincerity, academic honesty and methodological rigour throughout this research. I have been guided and supported by the valuable guidance and suggestion throughout the process of research.

I am very grateful to you for your constant guidance, constructive feedback, encouragement and very useful support during this research. Your mentorship has been an important factor in the successful completion of this research.

I respectfully submit this project for your kind supervision and approval.

Sincerely yours,



Shabiba Chowdhury

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DECLARATION OF THE STUDENT

I, Shabiba Chowdhury, hereby announce this project, entitled “Determinants of Continuance Intention Toward Generative AI for Learning and Skill Development: The Mediating Roles of Perceived Learning Effectiveness and Trust in AI” under the supervision of Mr. Ahmed Imran Kabir, Assistant Professor, United International University, to be a true and accurate copy of the thesis submitted by me for obtaining the degree of Bachelor of Business Administration (BBA), major in Business Analytics, at United International University.

I also certify that this research is my own and has not been presented, either in full or in part, to any other University or institution for the purposes of obtaining any degree, diploma or other academic award. Sources of information used in this study have been appropriately cited and attributed.



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ABSTRACT

This research concentrates on the factors that influence continuance intention of using generative artificial intelligence (GenAI) for learning and skill development. The study employs both performance-related and ethics-related determinants, such as the quality of the AI assistance quality, AI self-efficacy, AI transparency, bias perception, and privacy concern, and explores the mediating role of perceived learning effectiveness and trust in the AI. The research method employed was quantitative research using a structured questionnaire, and respondents who answered the instrument were 230 valid responses in the period April – May 2025. In data analysis, partial least squares structural equation modeling (PLS-SEM) was used in this study, which is a variation of structural equation modeling (SEM) that allows data to be analyzed using SmartPLS 3.2.8.

The results indicate that the quality of AI support exerted and the AI self-efficacy have positive and significant effects on the continuance intention, with a mediation effect of perceived learning effectiveness. The transparency paradox occurs when an increase in trust in AI also has a negative affect on continuance intention, as AI transparency does for trust in AI. The relationship between privacy concern and continuance intention was negligible and was not expected to be negative as previously suggested, whereas the relationship between bias perception was positively related to continuance intention. This study adds to the literature by combining the two elements of performance and ethics into one framework, and offers practical implications for developers, teachers, and policy makers in the realm of responsible and sustainable use of generative AI in educational settings.

Keywords: Generative Artificial Intelligence, Continuance Intention, Perceived Learning Effectiveness, PLS-SEM, AI Transparency.

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LIST OF ACRONYMS AND ABBREVIATIONS

Acronyms	Full Form
GenAI	Generative Artificial Intelligence
AAQ	AI Assistance Quality
ASE	AI Self-Efficacy
AT	AI Transparency
PC	Privacy Concern
BP	Bias Perception
PLE	Perceived Learning Effectiveness
TA	Trust in AI
CI	Continuance Intention
ECT	Expectation-Confirmation Theory
SCT	Social Cognitive Theory
PLS-SEM	Partial Least Squared Structural Equation Modeling
VIF	Variance Inflation Factor
NFI	Normed Fir Index
SRMR	Standardized Root Mean Square Residual

CHAPTER I: INTRODUCTION

I.1 Background of the Study

Radical changes in the field of technology-enhanced and self-paced learning have occurred due to the fast welfare of Generative Artificial Intelligence (GenAI). Because of publicly available large language models such as ChatGPT and several others, GenAI is bound to become a ubiquitous part of the higher education ecosystem as students of other fields begin using it in their writing, coding-assistance, exam-preparation, and problem solving (Almufarreh, 2024a; Mehrvarz et al., 2025). Earlier AI education systems were intelligent tutoring systems, learning analytics, and recommendation engines but, with the introduction of GenAI, AI has no longer been background analytics that can assist technology but instead an interactive partner, creating messages by demand (Gupta et al., 2025; Willis, 2024). According to the surveys in the higher education sector, students and teachers currently consider AI a key technology in the development of new skills, collaborative learning, and access to research, especially in the middle and high-income environment where the digital infrastructure is already developed (Kuleto et al., 2021; Sova et al., 2024). This mass adoption is of immediate concern not just to how fast the GenAI adoption would be but to how and why learners would continue to learn and acquire skills in the long run.

Generative AI in learning can be informally described as AI systems that can be executed to generate new content (i.e. explanations, examples, summaries, code or feedback) based on inputs of users, which are the ones processed and applied by students to their own work (Almufarreh, 2024a; Dwinggo Samala et al., 2025). GenAI facilitates the logical dialogue, unlike the traditional search engine or fixed e-learning posture, and learners can reduce the prompts, pose follow-up questions and scaffold the activities individually to write an essay or solve a quantitative problem (Mehrvarz et al., 2025; Yang et al., 2025). The use of these tools is also high in the first case because of the perceived convenience, perceived performance expectancy and hedonic motivation (H. Guo & Erdenebold, 2025; Masrek et al., 2025). However, the continuance intention the decision to persist in the use of GenAI as a steady feature of the studying behavior and not a novel phenomenon is the

true value of educational institutions and individuals (Purwita & Sari, 2025; Zhou & Zhang, 2024). The outcomes of this research organized grounded in Expectation-Confirmation Theory and UTAUT-derived models have once again proven that the continuance intention depends on the perceived performance, expectation confirmation, and satisfaction, as well as trust, and, therefore, continuance intention is among the central results of the AI-enabled learning environments (Mohd Rahim et al., 2022; Purwita & Sari, 2025).

Continuous research is adopted, in this respect, to explain the continuance intention through two prongs of the determinants. As per performance, the quality of the AI assistance may be delivered by the promptness and suitability of GenAI outcomes, and their intelligibility and applicability in helping the students to achieve their short-term academic tasks and long-term skill mastery. The GenAI research in the academic field addresses the claim that the content quality, perceived utility, and perceived accuracy may be discussed as the primary predictors of satisfaction and behavioral intention since students use the AI-generated content to better their knowledge and complete assignments (Almufarreh, 2024b; Dwinggo Samala et al., 2025). (Almufarreh, 2024a) also found that the accuracy and relevance of AI-generated content play a vital role in students' satisfaction with AI tools, suggesting that output quality is a key determinant of engagement. To accompany this, AI self-efficacy is the way learners feel they can effectively employ GenAI (e.g., creating the correct prompts, evaluating responses, and integrating feedback), which, like the technology self-efficacy, is also featured in the studies of social cognitive theory (Ahmed Zahrani, 2026; Gökçe Tekin, 2024). The research on chatbots and AI tools has suggested that the higher the self-efficacy an individual has, the more he or she perceives the easily useable, usefulness, and task-technology fit, which in turn result in an heightened need to use the AI in the process of learning or career progression (Ahmed Zahrani, 2026; Xiao et al., 2025; Yang et al., 2025). This combination of these performance-related aspects can be regarded as the side of GenAI use.

At the same time, a growing body of literature underlines the inadequacy of the utility to justify the additional application of AI; more are the moral and safety-related factors which

can shape the attitude and intentions of learners. The second group of determinants that may answer the question of whether it is safe and fair to use is the AI transparency, privacy concern, and sense of bias (Gupta et al., 2025; Willis, 2024). The explainability of AI systems and comprehension of its manner of generating outputs are the transparency, which can be used to counteract the black box aspect of the complex models and is the gateway to instilling user trust (Angerschmid et al., 2022; Gupta et al., 2025). (Angerschmid et al., 2022) stated that fairness and explainability in the use of AI in decision making are fundamental prerequisites for gaining user trust, especially in critical areas like education. The problem of privacy is connected to data gathering and holding it and subsequent application in other activities of the prompts and personal information, which is a timely one because institutions of higher learning and AI sellers store a lot of data about learners (Sova et al., 2024). Biases perception entails the realization of a user of algorithmic bias and/or hallucination and potentially, discriminatory or biased output, which can compromise the validity of AI as a fair learning companion (Gupta et al., 2025; Willis, 2024). Recent empirical research has found the fear of AI to in turn reduce the positive attitudes and perceived utility but the transparency and ethical design enhances the perceived trust and willingness to use AI tools (Mohd Rahim et al., 2022; Sova et al., 2024; Y. Zhang et al., 2025).

Notably, these performance and ethics related determinants do not operate independently; they mediate continuance intention using critical psychological states. In performance dimension, the concept of perceived learning effectiveness is a subjective manifestation of the fact that GenAI in effect enhances understanding, performance, and skills of the learners. Studies of AI-assisted self-directed learning and expectation-confirmation models state that perceived usefulness, satisfaction and perceived performance are the most influential predictors of continuance intention, and satisfaction and perceived gains are the most central predictors (M. Guo, 2024; Purwita & Sari, 2025; Zhou & Zhang, 2024). On the ethics front, trust in AI, manifested as the readiness to trust AI suggestions and outputs, is the mediator of the influence of transparency, privacy issue, and bias impression on usage choices (Abdelazim et al., 2025; Al-Rahmi et al., 2026; Y. Zhang et al., 2025). Higher education and organization learning studies indicate that under the influence of trust, the facilitating conditions, the performance expectation,

and the ethical perceptions are converted into the intentions to learn through AI (Ahmed Zahrani, 2026; H. Guo & Erdenebold, 2025). This study will explore a broad explanation of the continuance intention in terms of both the performance-focused and the ethics-focused perspectives of GenAI-based learning by introducing two constructs, namely, perceived learning effectiveness and trust in AI, as dual mediators.

I.2 Statement of the Problem

Although the potential of generative AI in education is obvious in terms of the increased personalization, accessibility, and efficiency, one issue can still be identified: the black box quality of GenAI poses a dilemma between usefulness and ethical concerns. On the one hand, learners gain significant advantages in terms of fast feedbacks, customized explanations, and customizable assistance in activities and subjects (Kuleto et al., 2021; Mehrvarz et al., 2025). In contrast, they tend not to understand how models are modelling responses, what data are being used, or what their individual requests and actions are being saved and reused and therefore raise long-term questions of transparency, privacy, and bias (Gupta et al., 2025; Willis, 2024). This paradox creates a psychological space that seems to be quite complex as learners might appreciate the support of GenAI and at the same time be reluctant to turn it into a permanent learning companion (Mohd Rahim et al., 2022; Y. Zhang et al., 2025).

Concerning performance, one of the main questions is whether GenAI indeed helps learn or just allows doing the work faster. Students can also create solutions or texts without having complete comprehension of the principles behind them, which is problematic since the use of GenAI might destroy deep learning without conducting critical usage (Dwinggo Samala et al., 2025; Gupta et al., 2025). (Zhou & Zhang, 2024) noted that there is a difference between the adoption-stage and the post-adoption model, as university student users of AI for self-directed learning were better predicted by perceived gains in knowledge, rather than perceived initial usefulness. Empirical studies indicate that performance expectancy, as well as perceived usefulness have a strong predictive quality in initial behavioral intentions, but continuance is more dependent on perceived performance and satisfaction, or whether learners feel that their knowledge and skills have actually been enhanced as a result of AI-based engagement (Purwita & Sari, 2025;

Zhou & Zhang, 2024). However, perceived learning effectiveness is not directly represented in many of the models in existence as a mediator between technical aspects, including assistive quality and self-efficacy and long-term continuance. Consequently, it is still unclear to what degree high-quality assistance and robust AI self-efficacy can be altered into the long-term use of GenAI in the form of the perception of relevant learning.

Ethical issues also make this image more complicated as they lead to the establishment of a trust gap between users and GenAI systems. Higher education research establishes substantial student worries regarding the confidentiality of data and their safety, as well as the misuse of their personal data, as these factors have a harmful affect on the positive attitudes and perceived usefulness of AI-tools (Sova et al., 2024). (Sova et al., 2024) research indicated that privacy and institutional data management issues had a profound impact on students' interest in using AI in learning. It is also evidenced that perceived trust is highly moderated by design, interactivity, and ethical protection, and in its turn, has a significant effect on behavioral intention to use AI-based chatbots and GenAI tools (Dewi & Nurcaya, 2025; H. Guo & Erdenebold, 2025; Y. Zhang et al., 2025). At the same time, the available literature on algorithmic bias and hallucinations focuses on the fact that these biasing of training information can lead to making unfair or erroneous judgments, which jeopardizes the truthfulness of AI as a reliable academic companion (Gupta et al., 2025; Willis, 2024). However, numerous empirical models do not focus on transparency, privacy, and bias per se but instead position them as a background factor that does not systematically enter the mediating equation of the effect of trust on continuance intention.

Another issue is that the existing studies have mostly focused on the initial adoption of AI and GenAI, and have typically applied TAM or UTAUT, or UTAUT2-based models to describe behavioral intention but provided less information on the progression between first-time usage and long-term habit. The adoption of AI chatbots, teacher preparedness, or student behavioral intention is usually the topic of studies covering the contribution of performance expectancy, effort expectancy, enjoyment, or facilitating conditions, and occasionally including trust as an additional predictor (Masrek et al., 2025; Pasupuleti et al., 2025). These models are not particularly common in performance factors and ethical risk perceptions, and dual mediators are seldom found in the same structural language

as seen in these models. The gap in the body of research that employs structural equation modeling (SEM) to justify the continuance intention towards GenAI with respect to learning and skill development based on the perceived learning effectiveness and trust in AI as mediating variables is notably significant. As a result, the discipline does not have a comprehensive view of the relationship between the quality of assistance, self-efficacy, transparency, privacy concern, and bias perception as they influence the choice of students to integrate GenAI into their lifelong learning processes.

I.3 Research Gap

Although there is a swift increase in the attention paid to AI and GenAI in the educational field, there are still several critical gaps. Numerous researchers consider the initial acceptance, behavioral intention, or satisfaction with the AI chatbots and tools, and many of them adopt the models, including TAM, UTAUT, or UTAUT2 (H. Guo & Erdenebold, 2025; Masrek et al., 2025; Xiao et al., 2025). (Masrek et al., 2025) said that the moral aspects of trust and perceived risk, however, have not been extensively discussed in these adoption models adding that these components are important with regards to initial behavioural intentions, as explained by the UTAUT II. The current continuance literature on e-learning focuses on the effects of such constructs as satisfaction, perceived usefulness, and confirmation yet does not pay much attention to the joint influence of the perceived risks of ethics and trust in generative AI application to learning (M. Guo, 2024). The ethical issues outlined in reviews of AI in education include information privacy, algorithmic bias, and governance, yet fail to provide a systematic relationship to the long-term goals of the use of GenAI as a learning and skill building tool (Kuleto et al., 2021; Sultana et al., 2025). Consequently, the knowledge on continuance intention as an entity that is understood concurrently through the prism of performance (quality of assistance and self-efficacy of AI) and ethics (transparency, privacy, and perception of bias) is limited, and the perceived learning effectiveness and trust in AI is the mediator (Xu et al., 2025). By filling in this gap, developers can create practical information about user behavior to develop superior tools and teachers and policymakers that need to develop responsible use policies.

I.4 Objectives of the Study

General Objective

To inspect the determinants and mediating factors that affect the continuance intention to use generative AI to learn and develop skills in university students.

Specific Objectives

- To determine the effect of quality of AI assistance and AI self-efficacy on the perceived learning effectiveness of users using generative AI as a learning and skill acquisition tool.
- To investigate the effect of AI transparency, privacy perceptions, and bias perception on the trust of the users in generative AI in education.
- To establish the direct impact of perceived learning effectiveness and trust toward AI on the continuance intention of students to use generative AI to learn and gain skills.
- To examine the mediating effects of perceived learning effectiveness and trust in AI in relations between (a) AI assistance quality and AI self-efficacy and continuance intention (b) AI transparency, privacy concern, and bias perception and continuance intention.

I.5 Research Questions

To accomplish this goal, the research is led by three research questions:

RQ1: What is the result of the learning-related variables (quality of AI assistance, AI self-efficacy) on a perceived learning effectiveness of a user using GenAI to learn and develop his/her skills?

RQ2: How does the reliability level in Generative AI depend on ethical considerations (transparency, privacy concern, and bias perception)?

RQ3: Does the mediation of trust in AI and perceived learning effectiveness have a significant predictive value on the intention to persist in using GenAI as a skill development tool in the educational setting?

I.6 Scope and Limitation of the Study

Scope

- Focuses on students of universities as the active users of text-based generative AI in the academic and self-directed learning environment (Almufarreh, 2024b; Sova et al., 2024; Zhou & Zhang, 2024).
- The large language model (LLM) chatbots are examined because these are related to the support of writing, coding, explanation, and conceptual understanding (Mehrvarez et al., 2025; Yang et al., 2025).
- Researches the essential performance and ethical constructs, such as the quality of assistance, AI self-efficacy, transparency, privacy concern, perception of bias, perceived learning effectiveness, trust, and continuance intention (Gupta et al., 2025; Mohd Rahim et al., 2022).

Limitations

- Cross-sectional PLS-SEM design is not causally inferential, and it does not capture variations over time (M. Guo, 2024; Mohd Rahim et al., 2022).
- Self-reports can cause the bias in the responses and the common method variance (Kuleto et al., 2021).
- The sampling is limited to a specific context, which restricts the ability to generalize the research to other populations and other institutional contexts (Sova et al., 2024).
- Omits other reasons such as institutional support, AI literacy and peer influence which may affect continuance behavior (Ahmed Zahrani, 2026; Pasupuleti et al., 2025).

I.7 Definition of Key Terms

Artificial Intelligence: Artificial Intelligence (AI) is the term for computer systems that can do things that normally need human intelligence, such as learning, reasoning, problem solving, and decision making. The definition of AI in this study is technologies that facilitate learning and skill development by using intelligent interactions.

Generative Artificial Intelligence: Generative Artificial Intelligence (GenAI) is an AI system that can create human-like text, images, code and other information from user input. For this study, GenAI is defined as AI-based tools which learners use to aid in their academic learning and skill development.

AI Assistance Quality: The quality of AI assistance can be evaluated by users based on the accuracy, relevance, clarity, and usefulness of the responses provided by AI systems. Users are expected to find high-quality AI assistance to improve their learning experience and their usage of the platform.

AI Self-Efficacy: AI self-efficacy means individuals' confidence in their ability to benefit from generative AI technologies for learning, problem-solving, skill-building, and other purposes.

AI Transparency: AI transparency involves understanding how AI systems generate responses and the clarity of their processes, capabilities, and limitations. Users can make informed decisions on AI-generated content with more transparency.

Privacy Concern: Privacy concern refers to users' apprehension regarding the collection, storage, use, and protection of their personal information while using generative AI applications.

Bias Perception: Bias perception refers to how users perceive that AI outputs could contain bias toward or unfairness against people due to data or algorithm bias. Perceived Learning Effectiveness: Perceived learning effectiveness is about how users view the effectiveness of generative AI in enhancing their knowledge, understanding, academic performance and skills.

Trust in AI: Trust in AI is the trust users have for the reliability, credibility, and ethical practices of AI systems, which is reflected in their willingness to use the generated information and recommendations.

Continuance Intention: Continuance intention is the intention of the user to use generative AI tools and tools for learning and skills after the first use.

I.8 Organization of the Remaining Chapter

The remaining chapters are organized in the following way. The remaining chapters are arranged as follows.

The rest of this project consists of four chapters. The second chapter gives the literature review which encompasses the theories related to the study, empirical literature, hypotheses formulation and the conceptual framework of the study. Chapter Three outlines methodology of the research, which covers the research design, research context, questionnaire design, sampling technique, data collection procedures and data analysis methods. The results and analysis of the study will be discussed in Chapter Four. It is comprised of respondents' demographic profile, assessment of measurement model, analysis of validity and reliability, evaluation of structural model and hypothesis testing. The findings of the study are presented in the conclusion which is presented in Chapter Five. It also covers the implications (both practical and theoretical) and boundaries of the research, as well as recommendations for future research.

CHAPTER II: LITERATURE REVIEW

II.1 Relevant Theory

A comprehensive account of continuance intention to generative AI (GenAI)-supported learning is based upon Expectation-Confirmation Theory (ECT), the Technology Acceptance Model (TAM) and UTAUT theories, Social Cognitive Theory (SCT) and trust theory of human-computer interaction (HCI). All these theories describe the role played by performance-related factors and ethical perceptions on continuance intention via important mediating processes.

ECT-wise the continuance intention is stimulated by the post-adoption evaluations of perceived usefulness, confirmation and satisfaction (M. Guo, 2024; Zhou & Zhang, 2024). Perceived usefulness in AI-assisted learning is directly related to system and information quality that subsequently results in satisfaction and further usage (L. Zhang & Li, 2026). (Purwita & Sari, 2025) validated that within an expectation-confirmation (EC) model that applies specifically to the context of GenAI, expected performance outcomes, not the initial expectations, are the most significant determinant of the continuance intention of academic users of GenAI. In line with such reasoning, the perceived learning efficacy of the current study is conceptualized as a post-use assessment of how much GenAI enhances the learning performance of students, which makes it a mediator between the performance-related variables and continuance intention (H6, H7).

TAM and UTAUT also elaborate on the role of performance-related constructs on user evaluations and behavior. The determinants of behavioral intention are perceived usefulness and ease of use, performance expectancy and facilitating conditions (Kai et al., 2026). The satisfaction and intention to use are deeply affected by the quality of content, perceived accuracy, and utility and are GenAI-wise (Dwinggo Samala et al., 2025). In line with this, AI assistance quality will directly affect continuance intention and indirectly affect it by the perceived learning effectiveness (H1, H6).

As the SCT suggests, AI self-efficacy shows the trust of people in their capacity to make good use of AI tools (Bandura, 1997). The empirical data proves that self-efficacy positively affects the perception of usefulness, ease of use, and behavioral intention in AI

and educational technologies (Gökçe Tekin, 2024; Xu et al., 2025). Higher self-efficacy in GenAI learning environments enable users to produce more useful prompts, process outputs and control learning, which leads to higher perceived learning effectiveness and continuance intention (H2, H7).

In HCI and AI decision-making, ethical and risk-related constructs are based on trust theory. The perception of transparency, fairness, privacy protection, and reliability of the system determine trust in AI (Sultana et al., 2025; Y. Zhang et al., 2025). (Y. Zhang et al., 2025) found, in higher education students, that perceived transparency in the system and system reliability are the two key antecedents that lead to building trust that ultimately drives continued use of GenAI. According to the previous research, AI transparency enhances trust and user confidence, and privacy issues and bias impressions diminish trust and reduce the readiness to use AI systems (Gupta et al., 2025; Kuleto et al., 2021; Sova et al., 2024; Sultana et al., 2025; Willis, 2024). In educational AI, these ethical factors are also directly associated with behavioral intention (H. Guo & Erdenebold, 2025; Masrek et al., 2025). Thus, the effect of transparency will be positive on continuance intention, whereas the influences of privacy concern and bias perception will be negative (H3 - H5).

Notably, trust acts as an intermediary between perceptions of ethics and the outcome behavior. The empirical research shows that not only does trust directly predict AI adoption and continuance but also mediates the outcomes of system characteristics and ethical perceptions on user behavior (Mohd Rahim et al., 2022; Y. Zhang et al., 2025). In this regard, this research makes trust in AI a mental mediator between transparency, a concern on privacy, and a perception of bias to continuance intention (H8–H10).

In general, the combination of ECT, TAM/UTAUT, SCT, and the trust theory can offer an integrated model where performance-related variables (AI assistance quality, AI self-efficacy) can induce continuance intentions by means of perceived learning efficacy, whereas ethical perceptions (transparency, privacy concern, bias perception) can induce continuance intentions by means of trust.

II.2 Literature Survey

The increasing use of artificial intelligence (AI), especially generative AI (GenAI) in education has evoked a plethora of academic interest on many levels of learning and technology use. The current literature narrows down to four, thematically connected domains: (1) the transformative nature of AI in education and skill development, (2) determinants of performance influence perceived learning outcomes, (3) emergent ethical issues in AI use and (4) the role of trust in the mediation of human-AI interaction. The unity of these themes offers a clear and theoretically based framework into the analysis of continuance intention in AI-based learning environments coupled with the identification of critical gaps in the incorporation of performance, ethical, and psychological variables into a coherent analytical framework.

AI and GenAI are commonly known as disruptive in the field of higher education and skill acquisition, personalized learning, collaboration and accessibility (Kuleto et al., 2021). Intelligent tutoring systems and predictive analytics, which are examples of smart tools, improve learning performance and raise ethical concerns (Gupta et al., 2025; Willis, 2024). The system quality, the information quality and social interaction, and continuance intention are the results of perceived usefulness in self-directed learning, which results in motivation and satisfaction (Zhou & Zhang, 2024). Academic uses of generative AI, such as ChatGPT, are becoming widespread with perceived value, content quality, and trust being key factors regarding adoption and satisfaction (Memari & Rafat, 2025). Nevertheless, most of the studies prioritize initial adoption, and there is not much attention dedicated to long-term continuance (M. Guo, 2024; Singh & Suri, 2026).

The performance paradigm brings out the system quality role and user capability in perceived usefulness, satisfaction and continuance intention (M. Guo, 2024; Zhou & Zhang, 2024). Generative AI requires high quality and credibility of content since students actively learn using outputs (Almufarreh, 2024a). Behavioral intention will always be predicted using performance expectancy in the embracement of AI (Masrek et al., 2025; Mohd Rahim et al., 2022). The concept of self-efficacy also reinforces the perceived ease of use, usefulness, and intention to use AI tools (Gökçe Tekin, 2024; Xiao et al., 2025; Xu et al., 2025). (Gökçe Tekin, 2024) found using structural equation modeling that teachers

with higher AI self-efficacy showed significantly higher perceived usefulness and behavioral intention; and this can be logically extrapolated to students utilizing AI tools in an educational context. It is however rare to find studies that specifically attribute these factors to perceived learning effectiveness as a specific construct. That implies the necessity to base AI assistance quality and self-efficacy as predictors of perceived learning effectiveness, and subsequently determine continuance intention (Dewi & Nurcaya, 2025; Hasan et al., n.d.).

The issue of privacy, bias, and transparency are still crucial, although AI can lead to positive results (Abdelazim et al., 2025). Privacy issues may reduce trust and adoption when it comes to using and handling data. The impacts of algorithmic bias and unfairness can be unequal outcomes, thereby damaging the trust and perceived legitimacy (Amdan et al., 2026; Thompson et al., n.d.). As (Sultana et al., 2025) noted, the governance issues of transparency and privacy should not be viewed as two different technical considerations in the context of education, but as a unified challenge in regard to responsible AI analytics. Transparency and explainability should be entailed by the accountable use and responsibility of AI in education (Razzouki et al., n.d.). However, such ethical concerns are rarely integrated into empirical conceptions of continuance intention, meaning that there is a gap in knowledge of how privacy, bias, and transparency may affect the continuance of engagement (Sova et al., 2024; Sultana et al., 2025).

One of the key determinants of the relationship between the features of AI systems and user behaviors is trust that has a significant effect on adoption and continuance in education (Choudhuri et al., 2025; Li et al., 2025). (Li et al., 2025) discovered that users' social perception of the AI system (such as its reliability and communicative competence) strongly influenced the extent of trust built up after multiple interactions with the system in an interactive AI learning space. System-like and human-like trust increase interaction with AI-assisted learning (Y. Zhang et al., 2025). There is a robust development of trust on ethical dimensions such as fairness, transparency, and privacy and can be supported with explanations and responsible design (Sultana et al., 2025). Even though trust is commonly considered a direct predictor of intention, there is a paucity of studies that model trust as an intervening variable between the perception of ethics and continuance

intention. As a solution to this gap, the present research places trust as an intermediary between ethics and continuance as well as connects performance factors to perceived learning effectiveness within a single framework (Hasselwander & Lah, 2026; Kalimira & Jazayeri, 2026; Razzouki et al., n.d.; Sassenberg et al., 2026).

II.3 Hypotheses Development

AI Assistance Quality

The quality of AI assistance is its accuracy, relevance, clarity, and usefulness of the AI-generated content, as well as responsiveness and correspondence to the learning objectives (Almufarreh, 2024a). Cognitive loads are saved by good outputs and perceived usefulness and satisfaction in AI-assisted learning are enhanced (Zhou & Zhang, 2024). GenAI applications allow students to use quality and context-appropriate outputs to complete tasks (writing, coding, problem solving, etc.), improve their short-term performance and long-term skills (Kuleto et al., 2021; Willis, 2024). In line with the Task-Technology Fit theory, properly matched AI aid enhances the learning process and promotes the further usage (Yang et al., 2025). Hence, an increase in perceived quality of assistance should lead to an increase in continuance intention.

H1: AI assistance quality has a positive and significant effect on continuance intention to use generative AI for learning and skill development.

AI Self-Efficacy

AI self-efficacy means that learners have confidence in their capacity to successfully utilize the GenAI tools, such as the timely formulation, output evaluation, and task integration (Gökçe Tekin, 2024). Increased self-efficacy decreases levels of anxiety and increases perceived ease of use, usefulness and behavioral intention (Ahmed Zahrani, 2026). It is more probable that students who are highly self-efficacious will explore and refine outputs and realize an improved task-technology fit and learning outcomes. This trust encourages enhanced interaction and long-term learning and skill acquisition using AI.

H2: AI self-efficacy has a positive and significant effect on continuance intention to use generative AI for learning and skill development.

AI Transparency

The AI transparency is the level of user awareness of the way AI systems produce outputs (such as the use of data and decision-making) (Gupta et al., 2025). Transparency minimizes the black box effect and promotes accountability and trust in the users (Angerschmid et al., 2022). (Gupta et al., 2025) emphasized that being clear about the process the AI uses to respond helps reduce the black box problem and fosters a feeling of being informed and empowered by the students in AI-supported learning environments. Clear explanations and disclosure of system limitations are enhanced by trust in AI in education leading to adoption. Clear systems allow learners to be critical in assessing AI outputs and effectively employ it in the learning processes to enhance continuance intention.

H3: AI transparency has a positive and significant effect on continuance intention to use generative AI for learning and skill development.

Privacy Concern

Privacy concern is an expression of the fear of users on the issue of data collection, storage, and the misuse of personal information by AI systems (Chen et al., 2025). Although students acknowledge the positive aspects of AI, it is possible that they will use it less often because of surveillance, misuse of data, or insufficient control over the personal information (Sova et al., 2024). The threats to privacy may balance the perceived usefulness and dishearten continued use of AI tools (Deriba & Saqr, n.d.). Therefore, increased privacy concern is likely to decrease continuance intention.

H4: Privacy concern has a negative and significant effect on continuance intention to use generative AI for learning and skill development.

Bias Perception

Bias perception means that the users identify the possibility of inaccuracy, unfairness, or socio-cultural bias in the outputs of AI. Results filled with biasness and misleads may mitigate the sensing dependency and lessen the belief in AI systems (L. Zhang & Li, 2026). Such issues can demoralize the use of AI in critical learning activities by learners in education. The issue of unfairness and the absence of representative powers also support the negative view of AI systems ethically (Thompson et al., n.d.). Thus, the increased bias perception will diminish continuance intention.

H5: Bias perception has a negative and significant effect on continuance intention to use generative AI for learning and skill development.

Perceived Learning Effectiveness

Perceived learning effectiveness is an assessment of how AI enhances the level of knowledge, understanding, and skills among the users (Purwita & Sari, 2025). The quality of AI assistance and high self-efficacy allow learners to get valuable feedback, improve outputs, and have improved learning outcomes (Gökçe Tekin, 2024; Yang et al., 2025). According to previous studies, the answers to perceived usefulness and satisfaction, which are essentially the same concept as effectiveness, are the primary components of continuance intention. Perceived learning effectiveness, therefore, is a very important process of converting the elements of performance into long-term use.

H6: Perceived learning effectiveness mediates the relationship between AI assistance quality and continuance intention to use generative AI for learning and skill development.

H7: Perceived learning effectiveness mediates the relationship between AI self-efficacy and continuance intention to use generative AI for learning and skill development.

Trust in AI

Trust in AI is the readiness of the users to make decisions under uncertainty and rely on the AI results, depending on the perception of reliability, fairness, and ethical appropriateness (Emmanuel, n.d.). Transparency increases the level of trust because it leads to a better understanding, but privacy issues and prejudice views do the opposite

(Gupta et al., 2025; Septiawan et al., 2022). Empirical research proves that trust has a crucial impact on AI adoption and continuance and tends to mediate the impact of ethical and design-related factors (Madani et al., 2026; Peruchini & Gonçalves, n.d.). (Mohd Rahim et al., 2022) confirmed that trust is a critical mediator between the ethical design of the systems and students' ongoing behavioral intentions in the hybrid PLS-SEM and neural network study on the adoption of AI chatbots in higher education. The trust in GenAI learning helps users to evade risks and incorporate AI into the fundamental learning processes.

H8: Trust in AI mediates the relationship between AI transparency and continuance intention to use generative AI for learning and skill development.

H9: Trust in AI mediates the relationship between privacy concern and continuance intention to use generative AI for learning and skill development.

H10: Trust in AI mediates the relationship between bias perception and continuance intention to use generative AI for learning and skill development.

Continuance Intention

Continuance intention is a choice of users to remain loyal to a technology after its initial adoption (H. Guo & Erdenebold, 2025). It depends on its perceived usefulness, satisfaction, and trust, especially AI-mediated learning processes (Al-Rahmi et al., 2026). GenAI In GenAI situations, continuance intention is a measure of the overall effect of performance-related (learning effectiveness) and ethical (trust) regarding whether learners incorporate AI into long-term skill development.

II.4 Conceptual Framework

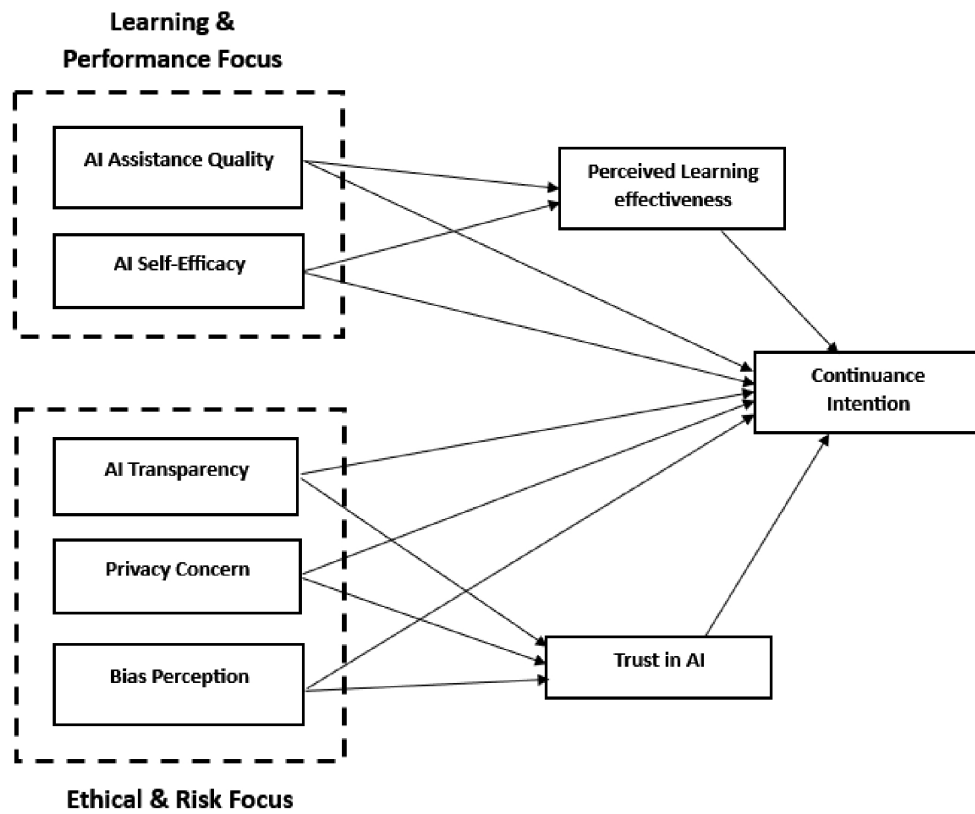


Figure 1 Framework of the Study

CHAPTER III: METHODOLOGY OF THE STUDY

III.1 Study Context

In the field of education and skill development, the use of generative artificial intelligence (GenAI) tools has revolutionized the way people collaborate with information, solve problems and enhance their learning experiences. AI systems like ChatGPT, Gemini and other systems are increasingly being used by students, professionals, teachers and others for educational and professional purposes. Although generative AI systems are becoming more popular, user continuation intention toward the use of these systems is a critical issue for researchers and practitioners.

The primary goal of this study is to investigate factors affecting people's intentions to continue using generative artificial intelligence for learning and skill development purposes. In particular, the study aims to investigate the connection between AI Assistance Quality, AI Self-Efficacy, AI Transparency, Privacy Concern, and Bias Perception with continuance intention toward the use of generative AI. Furthermore, the research seeks to realize how Perceived Learning Effectiveness and Trust in AI mediate between the relationship between learning perspective, ethical focus and continuance intention. This investigation will offer insights into the behavioral factors that simplify or hamper the ongoing adoption of technologies for generative AI in learning and skill development settings.

III.2 Research Design

This study was quantitative research with cross sectional survey design. A quantitative method was appropriate for this study because it was designed to assess the relationship between several variables and to test the hypotheses statistically. Primary data was collected from the respondents with structured questionnaire.

A partial least squares structural equation modeling (PLS-SEM) is used for data analysis. This data analysis technique in this study is a partial least squares structural equation modeling (PLS-SEM) with the software of SmartPLS version 3.2.8. The proposed conceptual framework has several latent constructs and mediational relationships, and simultaneous analysis was considered suitable for this study, therefore PLS-SEM was

used. The study further aims to primarily explain and predict the variation in continuance intention towards using generative AI (Sarstedt et al., 2021).

To evaluate the reliability of the items on the questionnaire, a pilot study was first conducted with 30 respondents, prior to the final survey. Cronbach's alpha was used to conduct reliability analysis in SPSS. Under each variable, there were four items. One item (AAQ3) was deleted from the AI Assistance Quality (AAQ) construct during the pilot test, since deleting the item increased the reliability coefficient of the construct. The questionnaire was then revised following the pilot study and afterwards sent out for the main data collection.

III.3 Questionnaire Design

This study used a two-part questionnaire. The first section collected demographic information of respondents, including gender, age, occupation, and AI usage frequency. The second part was the measurement of the study constructs. The constructs consisted of AI Assistance Quality (AAQ), AI Self-Efficacy (ASE), AI Transparency (AT), Privacy Concern (PC), Bias Perception (BP), Perceived Learning Effectiveness (PLE), Trust in AI (TA), and Continuance Intention (CI). Four indicators were used for each construct. Items were answered on a 5-point Likert scale from Strongly Disagree (1) to Strongly Agree (5).

III.4 Sampling and Data Collection

The sampling technique for this study was non-probability convenience sampling, which involved the collection of responses from individuals who had some prior experience with generative AI tools for learning or skill development activities. The choice of convenience sampling was deemed suitable because the study participants were those who were accessible and knowledgeable about generative AI technologies.

Data was collected using an on-line survey from April 2026 to May 2026. Initially, a total of 250 responses were collected. Following data cleaning and screening processes, 230 valid responses were used for the final analysis. Answers that were incomplete or were inconsistent or answers that were missing were not included.

The respondents consisted of various groups of people ranging from students, employed, businessmen, teachers, and homemakers. A diverse range of respondents provided their views on the intention to continue using generative AI technologies for learning and skill development, helping to offer a wider perspective.

The final number of respondents (N = 230) was deemed sufficient for PLS-SEM analysis, as it can be effectively analyzed within complex models with relatively small sample size (Ramayah et al., 2016).

III.5 Data Analysis Plan

Data collected were analyzed using SPSS software and SmartPLS software version 3.2.8. Demographic analysis and data screening were performed using SPSS, while pilot reliability testing was carried out using SPSS and PLS-SEM analysis was carried out by SmartPLS.

Demographic data analysis, reliability data analysis, measurement model analysis, discriminant validity data analysis, and structural model analysis were included in the analysis process. Indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were used to assess the reliability and convergent validity of the measurement items. Fornell-Larcker criterion, HTMT ratio, and cross-loadings were used to measure the discriminant validity.

The structural model was validated using path coefficients, bootstrapping, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2) and Variance Inflation Factor (VIF). The significance of the direct and indirect relationships between the constructs was tested by bootstrapping using 5,000 subsamples.

CHAPTER IV: RESEARCH FINDINGS AND ANALYSIS

IV.1 Profile of Survey Respondents

A total of 230 respondents was included in the sample. The gender ratio was skewed in favor of males (77.0%) to females (23.0%), which may be due to the technology-oriented academic setting of the study. Most of the respondents were between 18–24 (47.4%) and 25–34 (46.5%) years old, making up 93.9% of the sample, which is well-suited to the study's focus on the use of GenAI in universities. Students made up the largest occupational group (65.2%) followed by employed (30.4%). Of particular interest, 80.4% of respondents said they use AI daily and 12.2% weekly, suggesting that respondents are making use of AI in a meaningful way in their daily lives rather than simply responding to hypothetical scenarios.

Table 1 Demographic Profiles of Respondents

Characteristics	Frequency	Percentage
Gender		
Male	177	77.0%
Female	53	23.0%
Age Group		
Below 18	3	1.3%
18-24	109	47.4%
25-34	107	46.5%
35-44	7	3.0%
45 and above	4	1.7%
Occupation		
Student	150	65.2%
Employed	70	30.4%
Businessman	6	2.6%
Housewife	2	0.9%
Teacher	1	0.4%
Doctor	1	0.4%

AI Usage Frequency		
Daily	185	80.4%
Weekly	28	12.2%
Occasionally	11	4.8%
Rarely	6	2.6%
Never	0	0.0%
Total	230	

IV.2 Measurement, Validity, and Reliability of Data

The results of the Partial Least Squares Structural Equation Modeling (PLS-SEM) measurement model evaluation are shown in Table 2. The following psychometric properties are used to evaluate the quality of the measurement model: indicator loadings, internal consistency reliability (Cronbach's Alpha and Composite Reliability), convergent validity (Average Variance Extracted, AVE), and model fit indices (NFI and SRMR). All the criteria are measured against the existing thresholds in PLS-SEM literature (Fornell & Larcker, 1981; Sarstedt, Hair, et al., 2023)

Table 2 Measurement Model Assessment

Constructs	Items	Loading	Alpha	AVE	CR	R ²	Adj. R ²	NFI	SRMR
AI Assistance Quality	AAQ1	0.88	0.759	0.673	0.860			0.792	0.098
	AAQ2	0.737							
	AAQ4	0.837							
AI Self- Efficacy	ASE1	0.741	0.804	0.630	0.872				
	ASE2	0.804							
	ASE3	0.773							
	ASE4	0.853							
AI Transparency	AT1	0.705	0.781	0.600	0.857				
	AT2	0.789							
	AT3	0.784							
	AT4	0.818							

Bias Perception	BP1	0.842	0.836	0.671	0.891				
	BP2	0.806							
	BP3	0.843							
	BP4	0.784							
Continuance Intention	CI1	0.89	0.903	0.775	0.932	0.584	0.571		
	CI2	0.916							
	CI3	0.883							
	CI4	0.83							
Perceived Learning Effectiveness	PLE1	0.891	0.918	0.802	0.942	0.453	0.448		
	PLE2	0.857							
	PLE3	0.931							
	PLE4	0.901							
Privacy Concern	PC1	0.909	0.935	0.837	0.953				
	PC2	0.929							
	PC3	0.898							
	PC4	0.922							
Trust in AI	TA1	0.786	0.841	0.675	0.893	0.245	0.235		
	TA2	0.838							
	TA3	0.872							
	TA4	0.788							

Indicator Loadings

All loadings were at or above the criterion of 0.70 (Sarstedt, Hair, et al., 2023) ranging from 0.705 to 0.931, indicating all items are effective representations of their constructs.

Reliability

Cronbach's Alpha for all constructs was within the desired limit of $\alpha \geq 0.70$ (Nunnally, 1978), with the values ranging from 0.759 to 0.935. The internal consistencies of the constructs were good with Composite Reliability (CR) between 0.857 and 0.953, with all $CR \geq 0.80$, as recommended.

Convergent Validity (AVE)

The average variance extracted (AVE) scores ranged from 0.600 (AI Transparency) to 0.837 (Privacy Concern) with all scores being above the $AVE \geq 0.50$ criterion (Fornell & Larcker, 1981), indicating satisfactory convergent validity.

R² and Model Fit

R² values provide information on how much variance in the endogenous (dependent) constructs is accounted for by the exogenous (independent) constructs. In PLS-SEM, values of $R^2 \geq 0.10$ are regarded as having at least minimum substantive explanatory power, values of $R^2 \geq 0.25$ as weak, values of $R^2 \geq 0.50$ as moderate, and values of $R^2 \geq 0.75$ as substantial (Hair et al., 2011). Continuance Intention results in a R^2 of 0.584 (Adj. $R^2 = 0.571$). The model has a moderate to substantial level of explained variance ($R^2 = 0.571$). The perceived learning effectiveness ($R^2 = 0.453$, Adj. $R^2 = 0.450$) was also statistically significant. The coefficient of determination ($R^2 = 0.448$) indicates an acceptable fit. Trust in AI, on the other hand, has a relatively low R^2 of 0.245 (Adj. $R^2 = 0.235$). The three ethical predictors (transparency, privacy concern, bias perception) together explain only approximately 24.5% of the variance in trust ($R^2 = 0.235$), which means that the other factors are playing a role. This is above the minimum but also suggests that other factors not represented in the model (such as institutional trust and previous AI experience) could play a role in building trust.

The SRMR value of 0.098 is within the threshold of ≤ 0.10 (Henseler et al., 2015) and the NFI value of 0.792 is close to the ideal value of 0.90 but is still within PLS-SEM.

IV.3 Predictive Relevance and Effect Sizes: Q^2 and f^2

In PLS-SEM, the Stone-Geisser Q^2 values and Cohen's f^2 effect sizes are summarized in Table 3 to measure the relevance of a structural model in terms of prediction and substantive significance, respectively.

Table 3 Values of Stone-Geisser Indicator (Q^2) and Cohen's Indicator (f^2)

Constructs	Q^2	Continuance Intention (f^2)	Perceived Learning Effectiveness (f^2)	Trust in AI (f^2)
AI Assistance Quality		0.024	0.315	
AI Self-Efficacy		0.054	0.045	
AI Transparency		0.040		0.275
Bias Perception		0.049		0.011
Continuance Intention	0.415			
Perceived Learning Effectiveness	0.334	0.121		
Privacy Concern		0.003		0.006
Trust in AI	0.148	0.085		

Stone-Geisser Q^2 (Predictive Relevance)

To assess the predictive relevance of the model for endogenous constructs is the purpose of the statistic Q^2 which is estimated using blindfolding procedures. The threshold criterion is the value $Q^2 > 0$, the small, medium and large predictive relevance have the values

0.02, 0.15 and 0.35 respectively (Sarstedt, Hair Jr, et al., 2023). Continuance Intention has a Q^2 of 0.415 which means that the model is of high predictive relevance, meaning it is very good to predict this outcome variable. Perceived Learning Effectiveness also shows medium to large predictive relevance with $Q^2 = 0.334$ and Trust in AI has a small to medium predictive relevance of $Q^2 = 0.148$. The predictive validity of the structural model is confirmed by all three endogenous constructs that are larger than the minimum threshold $Q^2 > 0$.

Cohen's f^2 (Effect Sizes)

Cohen's f^2 coefficients indicate effect sizes for each individual predictor relationship in the structural model. Thresholds are $f^2 = 0.02$ (small), 0.15 (medium), and 0.35 (large) (Cohen, 2013). The analysis shows that there is a wide range of effect sizes over relationships.

AI Self-Efficacy ($f^2 = 0.054$) and Bias Perception ($f^2 = 0.049$) have small-to-medium effect sizes, and AI Assistance Quality ($f^2 = 0.024$) and AI Transparency ($f^2 = 0.040$) have small effects on Continuance Intention. The effects of Trust in AI and Perceived Learning Effectiveness are small to medium, with f^2 values of 0.085 and 0.121, respectively. Based on the negligible effect size ($f^2 = 0.003$), Privacy Concern shows a non-significant path in the structural model, which further supports its record.

AI Assistance Quality is the most substantively influential predictor of this mediator (PLE with large effect size, $f^2 = 0.315$). Contrastingly, the learning outcomes of AI Self-Efficacy have a small effect ($f^2 = 0.045$), indicating a comparatively minor impact on learning outcomes.

In the case of Trust in AI, the effect size calculated for this construct is very large ($f^2 = 0.275$), suggesting its strong influence on trust. Both the effect of Bias Perception on the mediator ($f^2 = 0.011$) and of Privacy Concern on the mediator ($f^2 = 0.006$) are negligible, in line with the non-significant paths in the hypothesis tests.

IV.4 Discriminant Validity Assessment

IV.4.1 Fornell-Larcker Criterion

The Fornell-Larcker criterion stipulates that the AVE square root (diagonal) must be more than the largest correlation between any two constructs in the square root diagonal (Fornell & Larcker, 1981).

Table 4 Fornell Larcker Criterion

Constructs	AAQ	ASE	AT	BP	CI	PLE	PC	TA
AI Assistance Quality	0.82							
AI Self-Efficacy	0.621	0.794						
AI Transparency	0.43	0.507	0.775					
Bias Perception	0.358	0.363	0.225	0.819				
Continuance Intention	0.62	0.569	0.326	0.452	0.88			
Perceived Learning Effectiveness	0.654	0.53	0.492	0.411	0.653	0.896		
Privacy Concern	0.232	0.161	0.066	0.378	0.224	0.205	0.915	
Trust in AI	0.524	0.452	0.485	0.178	0.528	0.497	-0.002	0.822

This was true for all eight constructs. For instance, the inter-construct correlation of the highest correlation, Privacy Concern (AVE root = 0.915) is much higher than that of the lowest, Bias Perception (AVE root = 0.378), and Continuance Intention (AVE root = 0.88) had the highest correlation, even though it was not as high as that of Privacy Concern. All constructs had satisfactory discriminant validity, as evidenced in these results.

IV.4.2 Heterotrait-Monotrait (HTMT) Analysis

All Heterotrait-Monotrait (HTMT) ratios were below the 0.85 limit, indicating discriminant validity of all construct pairs (Henseler et al., 2015).

Table 5 Heterotrait-Monotrait Ratio

Constructs	AAQ	ASE	AT	BP	CI	PLE	PC	TA
AI Assistance Quality								
AI Self-Efficacy	0.786							
AI Transparency	0.549	0.631						
Bias Perception	0.439	0.443	0.299					
Continuance Intention	0.729	0.664	0.375	0.519				
Perceived Learning Effectiveness	0.766	0.606	0.563	0.464	0.713			
Privacy Concern	0.271	0.192	0.127	0.425	0.24	0.218		
Trust in AI	0.646	0.533	0.587	0.209	0.586	0.549	0.096	

The maximum value of HTMT was 0.786 between AI Assistance Quality and AI Self-Efficacy, which is explained by the fact that the two variables overlap conceptually and is within the acceptable range. Overall, the lowest HTMT values were found for Privacy Concern, indicating the high level of conceptual uniqueness of this construct with respect to the other constructs.

IV.4.3 Cross-Loading Analysis

The 31 items loaded highest on their intended construct, which met the criterion of cross-loading for discriminant validity (Lohmöller, 2013).

Table 6 Cross Loadings of Measurement Items

	AAQ	ASE	AT	BP	CI	PLE	PC	TA
AAQ1	0.88	0.569	0.403	0.276	0.598	0.57	0.149	0.496
AAQ2	0.737	0.447	0.422	0.218	0.355	0.412	0.15	0.422
AAQ4	0.837	0.504	0.263	0.37	0.535	0.602	0.264	0.38
ASE1	0.511	0.741	0.302	0.266	0.446	0.357	0.02	0.366
ASE2	0.507	0.804	0.399	0.28	0.451	0.384	0.21	0.363
ASE3	0.392	0.773	0.448	0.328	0.403	0.402	0.201	0.291
ASE4	0.553	0.853	0.454	0.286	0.499	0.52	0.089	0.406
AT1	0.266	0.438	0.705	0.296	0.222	0.289	0.081	0.275
AT2	0.494	0.483	0.789	0.183	0.34	0.491	0.05	0.443
AT3	0.251	0.281	0.784	-0.006	0.156	0.321	-0.068	0.38
AT4	0.267	0.354	0.818	0.231	0.259	0.378	0.136	0.375
BP1	0.331	0.367	0.225	0.842	0.396	0.399	0.336	0.159
BP2	0.206	0.234	0.15	0.806	0.339	0.329	0.274	0.21
BP3	0.297	0.317	0.221	0.843	0.351	0.306	0.287	0.137
BP4	0.334	0.267	0.137	0.784	0.393	0.306	0.338	0.076
CI1	0.56	0.527	0.298	0.456	0.89	0.601	0.244	0.462
CI2	0.564	0.542	0.259	0.371	0.916	0.584	0.189	0.46
CI3	0.54	0.489	0.304	0.404	0.883	0.572	0.229	0.461
CI4	0.519	0.439	0.286	0.36	0.83	0.538	0.12	0.481
PC1	0.237	0.17	0.053	0.369	0.208	0.191	0.909	-0.035
PC2	0.221	0.16	0.064	0.364	0.228	0.211	0.929	0.025
PC3	0.217	0.159	0.095	0.339	0.179	0.18	0.898	-0.004
PC4	0.171	0.098	0.033	0.308	0.198	0.165	0.922	0.005
PLE1	0.626	0.48	0.498	0.432	0.609	0.891	0.199	0.439
PLE2	0.509	0.386	0.432	0.304	0.493	0.857	0.125	0.408
PLE3	0.608	0.495	0.413	0.379	0.623	0.931	0.202	0.452

PLE4	0.591	0.522	0.42	0.346	0.599	0.901	0.2	0.478
TA1	0.344	0.269	0.403	0.037	0.321	0.326	-0.075	0.786
TA2	0.387	0.343	0.389	0.082	0.326	0.318	-0.082	0.838
TA3	0.426	0.374	0.485	0.179	0.405	0.423	0.013	0.872
TA4	0.53	0.463	0.323	0.243	0.624	0.521	0.098	0.788

For example, the items of the AI Assistance Quality construct had a cross-loading of at most of 0.569 with any other construct, while the items of the PC1–PC4 construct had the near-zero cross-loadings with other constructs, ranging from 0.898 to 0.929. The theoretical logic behind the items of both variables suggests expected moderate cross-loadings (0.493–0.623) between the items of Perceived Learning Effectiveness and the items of Continuance Intention. In general, the item-level discriminant validity is supported across the measurement model.

IV.5 Assessment of Structural Model

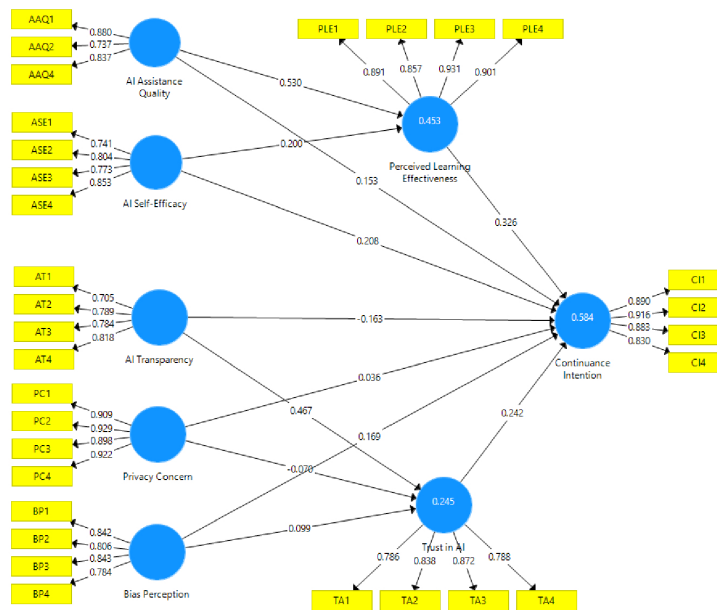


Figure 2 Path Diagram

IV.6 Hypothesis Testing (Direct and Indirect Relationships)

The results of the PLS-SEM structural model estimation are shown in Table 7, which displays the standardized beta estimates along with the standard error, t-value, p-value and hypothesis testing results for all the ten hypothesized relationships. The significance criterion adopted is $p < 0.05$ (two-tailed) which yields a t-value threshold of ≥ 1.96 . The direction of the relationship (positive or negative) is also tested in relation to the hypothesized direction.

Table 7 Structural Model Results (Hypothesis Testing)

Hypotheses	Relationships	STD. Beta	Std. Error	t-value	p-value	Decision
H1	AI Assistance Quality -> Continuance Intention	0.153	0.062	2.454	0.014	Supported
H2	AI Self-Efficacy -> Continuance Intention	0.208	0.064	3.256	0.001	Supported
H3	AI Transparency -> Continuance Intention	-0.163	0.057	2.864	0.004	Not Supported
H4	Privacy Concern -> Continuance Intention	0.036	0.045	0.787	0.431	Not Supported
H5	Bias Perception -> Continuance Intention	0.169	0.056	3.014	0.003	Not Supported
H6	AI Assistance Quality -> Perceived Learning Effectiveness -> Continuance Intention	0.173	0.037	4.712	0.000	Supported

H7	AI Self-Efficacy -> Perceived Learning Effectiveness -> Continuance Intention	0.065	0.030	2.154	0.031	Supported
H8	AI Transparency -> Trust in AI -> Continuance Intention	0.113	0.038	2.966	0.003	Supported
H9	Privacy Concern -> Trust in AI -> Continuance Intention	-0.017	0.018	0.924	0.356	Not Supported
H10	Bias Perception -> Trust in AI -> Continuance Intention	0.024	0.020	1.203	0.229	Not Supported

H1: AI assistance has a positive and significant direct relationship with continuance intention ($\beta = 0.153$; $t = 2.454$; $p = 0.014$). Higher quality AI outputs (in terms of accuracy, relevance, clarity) directly affirmed the students' desire to use GenAI further, aligning with TAM and Task-Technology Fit predictions.

H2: The continuance intention is best predicted by AI self-efficacy ($\beta = 0.208$, $t = 3.256$, $p = 0.001$). The study aligns with Social Cognitive Theory, finding that students who felt they could engage with AI outputs in prompting and evaluating are much more likely to continue using GenAI.

H3: The hypothesis was rejected since a significant, negative direct effect of AI transparency on continuance intention was found ($\beta = -0.163$, $t = 2.864$, $p = 0.004$). As users come to understand the nature of AI's outputs, it could paradoxically be the case that they will be more critical of the uncertainty and limitations of AI, making them less

inclined to trust it in the long term. This implies that transparency may have an indirect effect on continuance through trust (as validated in H8) instead of direct.

H4: There was no significant relationship found between privacy concern and continuance intention ($\beta = 0.036$, $t = 0.787$, $p = 0.431$). The coefficient is almost zero, indicating that students who use AI daily have become accustomed to compromising privacy when using data. Coefficient is near to zero, which shows the 'privacy paradox' in the use of technology, where users have become accustomed to making privacy compromises.

H5: Results showed a statistically significant positive relationship between bias perception and continuance intention ($\beta = 0.169$, $t = 3.014$, $p = 0.003$) which is contrary to the hypothesized negative relationship. If students are aware of algorithmic bias, they may be more advanced, experienced GenAI users who have strategies for checking the outputs of AI, leading them to be even more likely — not less — to use GenAI in the future.

H6: The perceived learning effectiveness has a strong connection with AI assistance quality and continuance intention, with the mediation effects of perceived learning effectiveness being statistically significant ($\beta = 0.173$, $t = 4.712$, $p < 0.001$). The indirect effect is larger than the direct effect (H1): This suggests that the direct utility perception was less the main driver of sustained use, with the perception of a real learning improvement being more so, and that this improvement is mainly attributed to the quality of the AI.

H7: The relationship between AI self-efficacy and continuance intention is proven to be mediated by perceived learning effectiveness with a significant value of 0.065, $t = 2.154$, and $p = 0.031$. This is a secondary effect that although small, it shows that self-efficacy also promotes continued usage by supporting the sense of educational progress in learners.

H8: AI transparency has a significant mediation effect on continuance intention through the factor of trust in AI, with a value of $\beta = 0.113$, $t = 2.966$, $p = 0.003$. Transparency has a negative direct effect on continuance (H3), but a positive indirect effect on continuance through increased trust (HCI trust theory).

H9: The mediated path through trust is non-significant ($\beta = -0.017$, $t = 0.924$, $p = 0.356$). Trust is not meaningfully affected by privacy concern in this sample, probably because of the normalization effect identified in H4.

H10: The path from bias perception to continuance intention through the trust construct is not significant ($\beta = 0.024$, $t = 1.203$, $p = 0.229$). Bias awareness works in a different way in this context, as it does not depend on the establishment of trust, but on other factors like critical user competence, which could influence the continued use.

Five hypotheses were confirmed (H1, H2, H6, H7, H8). The performance-based pathways, especially AI assistance quality and self-efficacy mediated by the perceived learning effectiveness, were the most affecting factors on the continuance intention. Both ethical pathways were more intricate: In addition to the direct pathway of trust on AI transparency (H3), a negative direct pathway was identified, though not as strong as the positive pathway, as did trust (H8) with the positive pathway. Neither privacy concern nor bias perception was present through the pathway of trust as hypothesized. The results highlight how important learning outcomes and self-confidence are in driving continued and sustained use of GenAI in the learning context, and how trust acts as a selective but significant stepping stone between ethics and continued use.

CHAPTER V: DISCUSSION

V.1 Conclusion

Based on this research, it can be concluded that the central factor to continuance intention regarding the use of generative AI in the educational context is the perception about the usefulness of AI for learning and confidence in using it, rather than ethical considerations. The results of the study highlight the following main findings:

It is concluded that both the quality of AI assistance and the students' self-efficacy have an impact on students continuing to engage with GenAI, independently and together, via perceived learning effectiveness. The hypothesized intervening mechanisms of perceived learning effectiveness (H6: $\beta = 0.173$, $p < 0.001$; H7: $\beta = 0.065$, $p = 0.031$) are not merely statistical artifacts, but rather a psychological truth: students are committed to using GenAI because they perceive it as effective in improving their learning, skills, or grades. This discovery supports ECT's main premise of expectation confirmation as the main driver for continuance behavior upon successful post-adoption outcomes, which results in perceived usefulness and satisfaction. When the outputs of GenAI are always accurate, relevant, and contextually appropriate, and when students have the self-efficacy to make use of this output effectively, the result is a strong sense of learning progress that results in long-term engagement.

The ethics-based route shows complexity and difficulty. While AI transparency positively builds trust in AI, which in turn supports continuance (H8: $\beta = 0.113$, $p = 0.003$), neither privacy concern nor bias perception operates through trust as originally hypothesized (H9 and H10 unsupported). However, both the direct effects of AI transparency (H3: $\beta = -0.163$, $p = 0.004$) and the direct effects of bias perception (H5: $\beta = 0.169$, $p = 0.003$) were not in the expected direction, and privacy concern had no significant direct effect at all (H4: $p = 0.431$). Overall, these findings indicate that ethical issues are not strongly linked to the decision to persist with the use of GenAI in a group of frequent, daily users of AI. Students seem to have bought into the compromise of privacy as a by-product of digital engagement; although the most familiar with the issue of algorithmic bias may be the most tech-savvy and competent users, that is likely the very cohort most likely to persist.

Theoretically, one of the most important findings of this study is the ‘transparency paradox’: the transparency of AI positively contributes to trust, but it also negatively impacts continuance intention directly. This is an intriguing paradox, as increased awareness about the workings of GenAI systems, such as their data utilization, their shortcomings, and the uncertainty that comes with AI can lead to cognitive discomfort — a critical questioning of whether they are safe to rely on — that outweighs the comfort they are believed to deliver through transparency. This finding contrasts with the widespread view found in the literature on AI ethics that transparency is a straightforward positive design feature, and it provides a call to action for further theorizing on the interaction between transparency and user psychology in contexts of frequent and embedded use of AI on a task.

The results for the relationship between bias perception and continuance intention (H5: $\beta = 0.169$, $p = 0.003$) shift the focus of algorithmic bias awareness from a negative to a positive perspective, suggesting that it can be viewed as a measure of GenAI literacy. Students who are aware that AI can produce biased or inaccurate results might have become more adept at verifying information, evaluating the tools, and understanding how well AI performs — which can paradoxically only reinforce their desire for continued use. The results have implications for the promotion of AI literacy education, as they indicate that exposing students to critically evaluating AI-generated content can potentially lead to more nuanced and enduring relationships with GenAI tools.

V.2 Theoretical Contributions

This research makes several important theoretical contributions to the current literature related to the use of AI, educational technology, and human-AI interaction. The study thus allows for a more holistic view of the continuance intention of using generative AI in learning and skill development settings, by combining the two types of determinants, namely performance-related determinants and ethics-related determinants, under one umbrella. The following is a list of the key theoretical findings of this study:

- This study makes several contributions to the literature on the adoption of AI, educational technology and human-AI interactions in the context of developing and empirically testing a dual-pathway model that combines performance-related and ethics-related factors into one model.
- Unlike many previous studies that were mainly concerned with the dimensions of performance expectancy, usefulness, or satisfaction, this study introduces ethical considerations concerning with privacy, transparency, and bias as well as putting perceived learning effectiveness and trust in AI on the bridge.
- The study finds that there is a paradox about transparency: Transparency has a positive effect on trust in AI, but a negative effect on continuance intention directly. Such a discovery implies that transparency can be a multi-faceted phenomenon with potentially positive and negative behavioural implications when implementing AI in the context of adoption.
- The results also contradict the long-held belief that a lack of perceived bias always deters the use of technology. The positive correlation between perceived bias and continuance intent suggests that when users are conscious of AI bias, they might persist with their use of the generative AI but do so in a more critical and responsible manner.
- This study is another contribution to the Expectation-Confirmation Theory (ECT) and Social Cognitive Theory (SCT) in the context of generative AI in learning. The findings indicate that perceived learning effectiveness and AI self-efficacy are important factors in the prediction of the continuance intention of the long-term use of generative AI technologies.
- The lack of significance for privacy concern is evidence of the privacy paradox in the use of generative AI. The results reveal that privacy risks are likely to be part of the norm for frequent users, leaving room for more research into the privacy behaviors in AI-supported learning environments.

V.3 Implications for AI Ethics and Responsible GenAI Use in Education

The findings of this study are not only technically and pedagogically significant but also have implications for the broader conversation about the ethics of AI in higher education, which is increasingly relevant as GenAI tools are increasingly being used in the academic environment at scale.

First, privacy paradox discovery is not only warning but also a discomfort. Students' privacy is not sufficiently protected, and ethical data governance is not superfluous given that it does not seem to be a significant constraint on the use of GenAI. It means that students are accustomed to sharing massive amounts of data — often without appropriate informed consent — and learning that this is a condition to unlocking the benefits of GenAI in their education. It implies that students are used to sharing large amounts of data — and sometimes doing so without informed consent — and have been taught that such data sharing is a prerequisite to accessing the educational benefits of GenAI. Institutions and policymakers bear the responsibility of securing the privacy of students who are not practicing privacy caution, and to provide structural safeguards that are not reliant on individual privacy choices.

Second, the fact that being aware of bias is correlated with continued use, rather than decreased use, means that the focus on informing students about AI bias (which is important) is not sufficient as a standalone risk mitigation measure. Awareness is not enough to create safe and equitable use of AI. Ethical AI guidelines for education need to shift from disclosure to building in students a practical ability to verify information, learn to triangulate information sources, and have a critical evaluation process that they can use in the immediate moment when they are using AI-generated information.

Third, the dual-pathway model underscores a fundamental conflict that can neither be eliminated by outright bans nor overcome by uncritical adoption of GenAI in education. Third, the dual-pathway model identifies a fundamental tension between the education benefits and ethical challenges of GenAI that cannot be solved by a ban or by uncritical endorsement. The model proposes that the most sustainable and responsible

way to adopt GenAI in higher education will be to develop student capabilities to gain meaningful learning from the use of these tools (self-efficacy, quality output requirements, and perceived learning effectiveness) while fostering the institutional trust landscape, the critical literacy skills, and the ethical governance frameworks that enable them to sustainably pursue this value without compromising fairness, privacy, and intellectual integrity.

V.4 Practical Recommendations

The results from this study have several practical applications for generative AI developers, schools, policies, and teachers. The findings underscore a need to enhance the quality of AI systems, build AI literacy, establish ethical governance of AI systems, and advocate for ethical practices of using AI in educational settings. The following are key practical recommendations that have come out of the study:

- The results indicate that developers of generative AI applications need to focus on boosting the quality, accuracy, clarity, and relevance of AI-generated outputs to improve the learning experience and continuance intention of the users.
- Developers need to prioritize creating pedagogically sound AI responses, enhancing the customisation of the content by topic, and minimizing the presence of incorrect or misleading answers potentially impacting on trust and perceived effectiveness of learning.
- Transparency in AI use is a delicate process that needs to be done wisely. Developers should explain contextual and user-friendly explanations of what AI has generated, while not overwhelming users with too much technical information.
- While the effect of privacy concern is not significant, privacy protection mechanisms, data policies and user control over personal data should be continued to be strengthened in responsible AI governance.
- Educators should foster a greater sense of AI self-efficacy by providing training sessions, workshops, and AI literacy programs to promote responsible and effective AI usage in education.
- Practical AI literacy should be incorporated into the academic curriculum for universities and educational institutions, where effective prompting methods,

critical evaluation of AI-generated content and awareness of AI limitations and biases will be taught.

- All institutions and policy makers need to have a clear policy and ethical guidelines on the use of generative AI, to facilitate responsible and balanced use of AI in educational contexts.
- The positive influence of the bias perception on continuance intention suggests that institutions should promote critical AI literacy and responsible interaction with the AI system, instead of banning the use of AI.
- Teachers and teachers' aides should illustrate the merits and drawbacks of generative AI in the classroom and the ability of students to critically discuss AI-generated information.
- Reflection, verification, and critical engagement with AI outputs may boost perceived learning effectiveness and AI self-efficacy in users' attitudes towards using AI for creative writing tasks. Reflection, verification, and critical engagement with AI outputs can enhance attitudes of users on the effectiveness of AI in creative writing tasks and their self-efficacy in using AI in creative writing tasks.
- Gradually introduce discussions about AI uncertainty, transparency, and bias to students and help them build realistic expectations and responsible behaviour regarding the use of AI.

V.5 Future Research Directions

This study has made key contributions to the theory and practice of mass communication, but there are other important areas which could be explored in future research.

5.5.1 Longitudinal Studies on Continuance Behavior

This cross-sectional study does not measure the cross section of continuance intention over time, but rather a cross section at a single point. Future studies should follow the same students over several semesters (longitudinal designs) to gain insight into the changes in perceived effectiveness of learning and trust in AI as students gain more experience with GenAI. This would help them to understand if the privacy paradox holds

true over time and if transparency's negative direct effect gets weaker over repeated use or if self-efficacy stabilizes without an effort to build it up.

5.5.2 Moderating Effects of AI Literacy and Prior Experience

The findings here indicate that the relationships tested in this study might be moderated by user sophistication and user experience with GenAI because bias perception had an unexpected positive relationship with continuance intention. Future studies should include a more explicit moderation variable, such as AI literacy, and examine if the relationship between ethics and continuance is significantly different for novice and experienced AI users.

5.5.3 Distinguishing Types of Transparency

Future studies should take into account the transparency paradox revealed in this study and break down the construct of AI transparency into its individual dimensions — process transparency (how the AI models produce their outputs), data transparency (what data it is taking), uncertainty transparency (how certain an AI is), and purpose transparency (why the AI was designed this way) — and investigate if these various forms of transparency create opposing effects on trust and continuance intention. This would enable to suggest design proposals more precisely and develop the theoretical reflection on transparency as a multidimensional phenomenon.

5.5.4 Expanding the Model with Additional Variables

The relatively low value of the R^2 for Trust in AI (0.245) shows that variables other than transparency, privacy concern and perceived bias have a significant role in determining trust in AI. In the future, institutional trust, AI experience, AI anthropomorphism perception, output consistency and social influence from peers and instructors should be added as additional predictors. Moreover, there are potential variables that could be included to enrich the performance pathway, including AI anxiety, cognitive load, and academic self-regulation, as well as the ethics pathway lengthened by the inclusion of ethical AI certification and/or regulatory awareness.

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APPENDIX

Independent Variables

AI Assistance Quality

1. AI gives answers that are useful for me.
2. AI responses are easy to understand.
3. AI usually gives correct information.
4. AI helps me finish tasks faster.

AI Self-Efficacy

1. I feel confident using AI tools.
2. I know how to ask AI the right questions.
3. I can check if an AI answer is correct.
4. I can use AI effectively for learning.

AI Transparency

1. I understand how AI creates answers.
2. AI explains its answers clearly.
3. AI is open about how it works.
4. I can understand why AI gives certain answers.

Privacy Concern

1. I worry that AI tools may misuse my data.
2. I feel my personal information may not be safe.
3. I am concerned about how AI stores my data.
4. Using AI may put my privacy at risk.

Bias Perception

1. AI sometimes gives biased answers.
2. AI may favor some opinions or groups.
3. AI is not always neutral.
4. AI can give misleading information.

Mediating Variables

Perceived Learning Effectiveness

1. AI helps me understand topics better.
2. AI helps me learn new skills faster.
3. AI improves my learning experience.
4. AI helps me improve my knowledge and skills.

Trust in AI

1. I trust the information AI provides.
2. I feel confident relying on AI.
3. AI usually gives reliable answers.
4. I feel comfortable using AI regularly.

Dependent Variable**Continuance Intention**

1. I plan to keep using AI in the future.
2. I will use AI regularly for learning or work.
3. I prefer using AI when I need help.
4. I intend to use AI as part of my daily routine.

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