Instrument Development for Assessing Continuance Intention toward Generative AI Tools in Education

Thamer Alshammari

Department of Information Technology, Computing informatics College, Saudi Electronic University, Riyadh, Saudi Arabia
Email: t.alshammari@seu.edu.sa
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***Abstract*—The objective of this study is to develop and validate an instrument identifying factors that affect the continuance intention toward generative Artificial Intelligence (AI) tools in the educational sector by integrating frameworks of the Information System (IS) Success Model and Expectation-Confirmation Model (ECM), as well as privacy concerns and trust. Constructs examined are perceived usefulness, trust, system quality, satisfaction, and other relevant dimensions. Expert reviews, pre-testing, and statistical techniques including Cronbach's alpha and Exploratory Factor Analysis using Principal Axis Factoring were employed to assess reliability and construct validity respectively, with reliability results exceeding 0.75. The final questionnaire contained 21 items addressing these dimensions. Even though the study does not test the significance of these factors, it identifies and operationalizes key constructs that will subsequently help future empirical research. This study provides a strong instrument that forms the foundation for understanding how Generative AI tools could be integrated into education to support personalized learning and improve accessibility. These insights can contribute to the improvement of user experience and more effective AI-based educational tools by policymakers, educators, and developers alike.**

***Keywords*—generative Artificial Intelligence (AI) in education, satisfaction with AI tools, AI continuance intention**

I. Introduction

In just a few years, Generative Artificial Intelligence (AI) has surged from a speculative technology to an essential collaborator in the classroom, with tools like ChatGPT, Gemini, and Copilot now powering teaching, learning, creativity, and productivity across global education systems. ChatGPT serves as a personalized tutor and writing assistant, helping students craft essays and instructors design lessons. Meanwhile, Gemini and Copilot support multimodal features, producing visuals and other creative outputs that enhance engagement and creativity in education. Currently, 80% of students worldwide report using Generative AI in their studies, with more than half using it daily or weekly. ChatGPT alone is used by 89% of students for homework and assignments [1, 2]. At prestigious universities, over 80% of students have adopted AI academically within two years of ChatGPT's introduction [3]. On the educators' side, about 60% of teachers have integrated AI each week, relying on it for research, lesson planning, and content creation, even saving up to 44% of time on administrative tasks [2]. The AI-in-education market reflects this momentum, projected to reach USD 32.7 billion by the end of 2025 [4]. This swift adoption underscores that Generative AI is not just part of the future of education; it has become a central force shaping modern teaching, learning, and academic innovation.

Although Generative AI tools are rapidly adopted in education, there is a limited understanding of the factors that influence continuance use beyond the initial adoption phase. While students and educators are quick to embrace tools like ChatGPT, Gemini, and Copilot for teaching and learning, concerns regarding trust, data privacy, and ethical usage impede their sustained integration. Studies indicate that many users remain skeptical of the accuracy and reliability of AI outputs, with instances of misinformation or "hallucinations" raising doubts about system quality and overall satisfaction [5, 6]. Privacy concerns are equally critical, as the collection and storage of sensitive student data raises concerns for institutions [7]. Additionally, despite increasing adoption, there is a lack of comprehensive and validated measures to assess continuance intention, the willingness of students and educators to use these tools consistently over time. Without a systematic framework to evaluate factors like trust, usability, satisfaction, and ethical concerns, ensuring the sustainable use of Generative AI in education remains challenging, underscoring a critical gap in the literature.

Despite the scholarly interest in the application of Generative AI in teaching, the majority of studies are limited to single theoretical frameworks like the Technology Acceptance Model (TAM), Information System (IS) Success Model, or Expectation-Confirmation Model (ECM), which do not provide a comprehensive view of the dynamics of adoption. For instance, Ghimire *et al.* [8] used TAM and Innovation Diffusion Theory to examine the perceptions of educators and emphasized the perceived usefulness and ease of use, but left out the crucial aspects of trust and privacy [9]. Furthermore, Kraisila *et al.* [10] used TAM among Thai students and confirmed the effect of expected benefits, although their model did not offer cross-construct variables such as satisfaction or risk. Trust, privacy and continuance intention are rarely considered in other studies devoted to the performance expectancy and social influence (e.g. [11, 12]). Consequently, there are limited studies that integrate these constructs into a single framework, which has left a research gap of how cross-construct relationships, including the relationship between perceived usefulness, trust, and privacy, affect the long-term adoption of Generative AI in education.

This research aims to create and validate a reliable measurement scale to assess the adoption and continued use of Generative AI tools like ChatGPT, Gemini, and Copilot in education. Unlike previous studies focused on individual models, it integrates frameworks and external factors, the IS Success Model and ECM, as well as privacy concerns and trust, to provide a more comprehensive understanding. The main constructs considered by the study are Perceived Usefulness (PU), Information Quality (IQ), System Quality (SyQ), Privacy Concerns (PC), Trust (T), Satisfaction (S), and Continuance Intention (CI). Exploring the interconnection among these factors, the study aims to

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provide evidence-based knowledge that may inform educators, policymakers, and developers on the sustainability and effective use of Generative AI in education. The following are the contributions of this study:

- Develops and validates a measurement instrument for adoption and continuance intention.
- Integrates theoretical frameworks and external factors (IS Success Model, ECM, privacy concerns, and trust) into a unified model.
- Provides insights for educators, institutions, and policymakers on responsible AI integration.
- Offers guidance to enhance trust, system quality, and user satisfaction for sustainable adoption of Generative AI tools.

Research Question: What factors influence users' intention to continue using Generative AI tools in the education sector?

II. Literature Review

Generative AI, such as ChatGPT, Copilot, and Gemini, is transforming the educational landscape by changing the creation and consumption of educational content. These tools provide an unprecedented opportunity for personalization, creativity and administrative automation. But there are numerous factors that affect their use in the education sector. This literature review examines the factors that influence the adoption of these tools, including key models of IS success and ECM, empirical research, challenges and gaps.

Generative AI has become increasingly popular in the field of education over the past few years, especially with the creation of image generators and Natural Language Processing (NLP). An example of such research was conducted by Alammari [13] on the use of Generative AI tools in the Saudi Arabian higher education system and the students and faculty attitudes towards the use of Generative AI. The author observed the potential of such tools in facilitating learning activities and enhancing educational outcomes, yet also raised some severe concerns regarding data privacy and the possibility of AI becoming a threat that could overtake the traditional teaching process.

At the institutional level, Aldossary *et al.* [14] covered the attitudes of the Saudi university students regarding the Generative AI technologies in education, the awareness, acceptance, and perceived application of AI in improving the educational outcomes. The study results demonstrated that the attitude towards the usage of AI tools is positive because the students know that they can improve the perception of some complicated concepts and the quality of the learning process in general. Another concern was the ethical considerations and necessary guidelines when using AI. Continuing on this, Alshahrani *et al.* [15] explored the use of AI tools in architectural education and found that AI could potentially automate the workload through such functions as blueprint development and rendering. Another point that was emphasized is that faculty members should be trained on AI tools to become as effective as possible in the classroom. Nevertheless, the research observed that there is no standardized system to incorporate AI in architectural education, which has impeded its mainstream adoption.

Continuing to examine the effect of Generative AI on creativity, Fares [16] conducted a study that examined the adoption of AI tools such as MidJourney, Stable Diffusion, and DALL·E (a text-to-image generative AI model developed by OpenAI) in interior design education. The objective of the study was to determine the impact of AI on creativity and design thinking among students. In a multi-stage model, the learners were involved in AI-assisted thinking, refining, and creating their own final projects. The outcomes showed that AI tools expanded creative possibilities, visualized design rapidly, and promoted the iterative thinking process. Nonetheless, disadvantages included the inability of AI to comprehend, the inaccuracy of output, and authorship issues within the creative process.

The potential effect of Generative AI implementation in the educational process has been examined through various theoretical lenses. An example is that Dahri *et al.* [17] examined how ChatGPT could be viewed as acceptable for Metacognitive Self-regulated Learning (MSRL) among pre-service teachers. Based on a mixed-method and extended TAM approach, the paper also found that personal competence, social influence, and perceived usefulness characteristics significantly influenced the intention related to the use of ChatGPT among students. The research identifies the potential of ChatGPT to restructure MSRL and teacher training.

TAM was also applied to examine how ChatGPT can be used to learn the English language among Saudi university students by Alotaibi *et al.* [18]. The analysis revealed that students perceived ease of use and usefulness as being influential in their intention to adopt AI tools. It suggested the addition of AI to the language learning curriculum and recommended that students be educated on how to best use them. At the same time, Mohamed *et al.* [19] investigated the acceptance of Generative AI tools and associated anxiety among nursing students in four countries of the Middle East (Egypt, Jordan, Saudi Arabia and Yemen). This study extended TAM by incorporating anxiety towards AI as an emotional factor. Findings revealed that performance expectancy, as well as effort expectancy, positively contributed to behavioral intention to use Generative AI tools, whereas anxiety moderated these relationships.

In this context, Strzelecki [20] studied the primary motives that determine the readiness of Polish university students to use ChatGPT based on an extended version of the UTAUT2 methodology. The paper referenced that Hedonic Motivation, Habit and Performance Expectancy had a significant influence on Behavioral Intention, and that Behavioral Intention and Habit had a significant impact on Use Behavior. The results showed that the model explained 72.8% of the variance in Behavioral Intention, and 54.7% of the variance in Use Behavior. It is important to highlight the regular use of AI tools and their benefits within higher education based on this evidence. Likewise, Sobaih *et al.* [21] used the UTAUT2 model to investigate the intentions of Saudi university students to adopt ChatGPT. Through their analysis, they found three key factors that influence the students' readiness to utilize Generative AI tools: performance expectancy, effort expectancy and social influence. This research highlights the importance of taking the local cultural and educational context into account when implementing AI adoption models.

Moreover, Aldreabi *et al.* [22] considered what leads to student adoption of Generative AI tools in higher education.

Applying an extended UTAUT2 model, this study revealed some of the key determinants, including performance expectancy, effort expectancy, hedonic motivation and habit. The evidence implied that these jointly affect the behavioral intention of students to utilize Generative AI tools, and thus an understanding of these determinants is a pressing need in promoting AI use in the academic environment. Lastly, Ngo *et al.* [23] used the ECM to evaluate factors that governed students to continue using ChatGPT and feel contented with the technology in education. In surveying 435 students in eight Vietnamese universities, his research found that expectation confirmation and perceived usefulness positively influenced satisfaction and continuance intentions to continue using ChatGPT. Remarkably, perceived usefulness proved not to be directly correlated with satisfaction, which implies that other factors such as trust and reliability may be of considerable importance.

Empirical studies provide valuable real-world insights regarding the implementation of Generative AI tools in learning environments. Alzahrani *et al.* [24] followed this procedure on a large scale by surveying multiple universities in Saudi Arabia to determine the extent of AI tools usage in the curricula. The analysis determined that, although most of the instructors and students were aware of the existence of AI tools, they did not use the tools because of the absence of training and technological facilities. The study noted the necessity to implement special policies to help implement AI in the educational environment.

In medical education, the research by Alghamdi *et al.* [25] addressed the attitudes of Saudi medical students concerning AI in the medical field in terms of perceived usefulness, ease of use, and effect on clinical practice. The questionnaire conducted among 1212 students across 32 Saudi Arabian universities showed that there was a conviction on the importance of AI, but that it was evident that AI education had not been adequately integrated into the curriculum. Such gaps include a lack of understanding of the concept of AI, the absence of practical knowledge of using AI tools, and inconsistent training in AI during medical studies. Additionally, Sarabdeen [26] published a research study where they evaluated the use of AI tools to provide law education and mainly identified the use of ChatGPT in legal research. The study revealed that AI technologies were extremely useful in conducting preliminary research and identifying case law. However, it was not welcomed by all educators since the traditional educators felt that it would interfere with traditional teaching. This brings out the difficulty of harmonizing AI integration with a traditional academic structure.

Mishra *et al.* [27] compared the developments of chatbot technologies with the recent Generative AI chat preferences, such as ChatGPT. The research reviewed natural language processing, Natural Language Generation (NLG), and machine learning, as well as their integration into chatbots. It also identified the uses of chatbots in the fields of education, healthcare and business and identified limitations such as biases in the answers generated by an AI, the inability to deliver contextual understanding, and difficulties in ensuring ethical and accurate interactions. The review acknowledged the potential of AI-driven chatbots but considered them in light of their limitations that must be addressed.

In addition, Simaremare *et al.* [28] conducted a survey to examine the diffusion of the Generative AI technologies among the students of Institut Teknologi Del, Indonesia. It was revealed that 70.96% of students had heard about Generative AI tools, and 98.96% of them had used this tool to facilitate their learning. The most popular Generative AI tools were GitHub Copilot, OpenAI ChatGPT, Codex, Grammarly, and ChatPDF. The authors summarized that Generative AI has become one of the essential aspects of everyday educational procedures and can contribute to the education system in the future. Nevertheless, the study established limitations, including the fear among students that the introduction of AI would replace human teachers as well as over-dependence on AI learning tools.

The positive impacts of Generative AI tools in education are numerous. They enable personalized learning by tailoring content to learners' specific needs and preferences. In addition, Generative AI promotes creativity, and thus, a student can participate in innovative projects, which were restricted by the capabilities of the traditional tools earlier. According to Sobaih *et al.* [21], AI tools can also considerably decrease the administrative burdens of educational institutions, contributing to the general efficiency of the educational institutions. Despite these opportunities, there exist several challenges. The ethical concerns about privacy, security, and the potential misuse of the AI-generated content continue to remain a top priority [13]. One of the main challenges of using AI tools as implied by Alotaibi *et al*. [18] is the risk of the human touch of teaching being lost due to the tools. Although much progress has been made, there remain serious concerns regarding the long-term impacts of Generative AI tools on educational outcomes. Longitudinal studies are needed to establish the impact of these tools on the knowledge building of students and their practice in instruction in the long term. Further research is also required to understand how AI tools can be effectively used in various education systems and disciplines.

The current literature reflects an increasing interest in using Generative AI in education, specifically, the opportunities and challenges that have been witnessed in Saudi Arabia. Despite the fact that AI-based applications, including ChatGPT, Gemini, and Copilot, have great potential, it can be successfully deployed by addressing a great number of challenges, such as technological limitations, resistance among faculty members, and ethical concerns. Addressing these gaps could contribute to wider adoption of AI in education and carry its benefits to more learning situations.

A. Proposed Framework

The research establishes an integrated framework through which the IS Success Model and ECM combine with Privacy Concerns and Trust as external elements to address existing research gaps. The IS Success Model enables assessment of system performance through its measurement of Information Quality and System Quality components while the ECM shows how users develop satisfaction through their actual experiences with the system. The educational sector requires both models to determine how students will continuously use AI tools for their studies. In the proposed model, the quality elements, information quality and system quality, alongside perceived usefulness, form a causal sequence that leads to user satisfaction, which subsequently drives users' continuance intention. The proposed model incorporates Privacy Concerns and Trust as external elements to address the specific ethical and data protection needs of Generative AI in educational settings which traditional models fail to address. Table 1 summarizes the existing work on GenAI adoption in the education sector.

Table 1. Summary of existing studies on generative AI adoption and use in education

Author & Year	Objective	Dataset	Methodology	Results	Limitation	Findings
Alotaibi *et al.* [18] (2025)	Factors influencing ChatGPT use among Saudi EFL learners	184 learners (Saudi Arabia)	Survey + SEM, TAM (PU, PEOU, Attitude, BI, AU) with demographics	TAM path confirmed; demographics (esp. gender) influenced adoption	Small sample, cross-sectional, no qualitative follow-up	ChatGPT adoption shaped by TAM factors & demographics, need tailored training
Mohamed *et al.* [19] (2025)	Study Generative AI acceptance, anxiety & behavioral intention in nursing education (Middle East)	1055 nursing students (Egypt, Jordan, KSA, Yemen)	Cross-sectional survey + SEM. Extended TAM (PE, EE, FC, SI + Anxiety)	75% BIU variance, all factors significant, anxiety strongly moderated ($\beta = 0.552$)	Cross-sectional design limits causal and temporal insights.	Reducing anxiety & strengthening support/social influence key to Generative AI adoption
G. Fares [16] (2025)	Examine AI as a collaborative partner in the teaching of interior design.	The sample is not specified	Multi-phase case study: precedent research, AI ideation, iterative refinement, final projects.	Expanded creative boundaries, iterative thinking, rapid concept visualization.	AI's limited contextual awareness, precision issues, and ethical authorship concerns.	AI empowers creative exploration but demands AI literacy, critical evaluation, and must be integrated with traditional design practice.
Alshahrani *et al.* [15] (2025)	Examine AI integration in Saudi architectural education	160 students, 32 faculty (Umm Al-Qura Univ.)	Quantitative survey + regression analysis	Students are enthusiastic, faculty cautious about creativity; both support integration	Single institution, limited scope, tools unspecified	Need training/workshops. AI should support creativity
Sobaih *et al.* [21] (2024)	Examine how well-received ChatGPT is by students in Saudi higher education.	520 students (public university)	Quantitative survey with UTAUT2 model	PE, SI, EE positively influenced BI; BI mediated to actual use; FC had negative/insignificant effects	Single university, limited support context	Performance Expectancy, Social Influence, and Effort Expectancy all had significant positive direct effects on Behavioral Intention to use ChatGPT.
Alammari *et al.* [13] (2024)	Evaluate educators' perceptions and readiness for Generative AI in Saudi higher education	Surveys & interviews with educators (sample not specified)	Mixed-methods (quantitative survey + qualitative interviews)	Awareness correlated with use; ~50% educators showed readiness; highlighted collaboration & innovation potential	Limited participant details, possible bias, ethical and implementation issues underexplored	Educators are ready and motivated. Generative AI is seen as supportive, but ethics and policy gaps remain
Aldossary *et al.* [14] (2024)	Assess Saudi students' perceptions of Generative AI in education	1390 students from 15 Saudi universities	Quantitative survey (descriptive analysis)	High awareness and acceptance; benefits in learning, feedback, skills, SDGs; disciplinary differences	Self-report bias, cross-sectional design, and low ethical awareness	Students are receptive to Generative AI; ethical use and policy frameworks need strengthening
Ngo *et al.* [23] (2024)	Investigate factors influencing satisfaction and continuous ChatGPT use in education	435 students across 8 Vietnamese universities	Survey (Likert) + CFA & SEM, ECM Model	Students kept using ChatGPT when expectations were met, and they were satisfied; usefulness alone didn't boost satisfaction.	Limited sample data.	Meeting expectations is more important than usefulness alone for long-term use.

Note: AU = Actual Use, BI = Behavioral Intention, BIU = Behavioral Intention to Use, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, PE = Performance Expectancy, EE = Effort Expectancy, FC = Facilitating Conditions, SI = Social Influence, TAM = Technology Acceptance Model, SEM = Structural Equation Modeling.

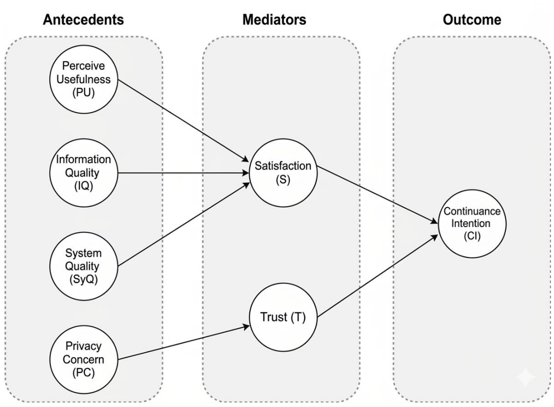

Fig. 1. Integrated proposed framework.

In particular, the perceived usefulness provided by the ECM, as well as the Information Quality and System Quality of the IS Success Model, are represented as antecedents of Satisfaction. Meanwhile, Privacy Concerns are theorized as antecedents of Trust, and both Satisfaction and Trust exist as core mediators that directly impact Continuance Intention. This combination model thus provides more explanatory insight than any single theoretical perspective as it simultaneously tackles system performance, user cognition, and ethical aspects of AI integration in education.

The proposed framework is shown in Fig. 1, which shows how different constructs connect and how Satisfaction and Trust work as mediators to influence Continuance Intention.

III. Methodology

A. Research Design

Purpose: This study aimed to develop and validate an instrument that measures the factors affecting users' intentions to continue using Generative AI platforms and tools in education. The research integrated these domains because both play increasingly central roles in educational technology, with Generative AI facilitating administrative processes while also enhancing learning experiences.

Approach: Following a quantitative approach, the study developed a precise measurement tool to measure continuance intentions. The instrument covers both administrative and pedagogical uses of Generative AI, as these tools support tasks such as scheduling and form-filling while also enhancing learning outcomes through personalized assistance.

Data Collection: The design of a survey instrument is based on already established theoretical models, such as the ECM, and the use of the IS Success Model, which have been applied to develop measures of user intention in the contexts of Generative AI and other technologies.

B. Instrument Development

Conceptualization: Constructs about Generative AI tools' continuance intentions are conceptualized from the extant literature. These include the following:

- **Perceived Usefulness (PU):** How users perceive that AI tools increase their academic performance.
- **Information Quality (IQ):** The accuracy, completeness, and timeliness of the information presented by AI tools.
- **System Quality (SyQ):** The performance of the platforms based on usability and reliability.
- **Privacy Concern (PC):** Users' concerns about data security, personal information protection, and the risk of unauthorized access when using AI tools.
- **Trust (T):** That personal data is in the safe hands of AI platforms.
- **Satisfaction (S):** A general positive perception concerning the employment of tools.
- **Continuance Intention (CI):** Intention to continue using AI tools in the future.
- **Operationalization:** The operationalization of each construct into items that will be measured will depend on previous relevant models. Thus, allowing the instrument to measure users' satisfaction and trust, and their effect on continuance intention.

To investigate the use of generative AI tools in education, Table 2 presents the constructs along with their definitions and examples.

Table 2. Constructs, definitions, and example items for investigating generative AI use in education

Construct	Definition	Example Item
PU	The degree to which users believe AI tools improve performance.	"Using AI services improves my ability to access resources".
IQ	Refers to the accuracy, completeness, and timeliness of the information provided by the tools.	"Generative AI tools provide accurate information".
SyQ	Highlights the usability and reliability of AI tools	"Tools for Generative AI are simple to use".
PC	The degree to which users are concerned about the security, confidentiality, and potential misuse of their personal data when using AI tools.	"I am concerned about the privacy of my personal data when using Generative AI tools".
T	Reflects confidence in the secure and reliable management of data by platforms	"AI platforms are reliable to follow my private data".
S	It reflects a generally favorable emotional reaction to the tools' use.	"I am satisfied with the performance of Generative AI tools".
CI	Intention to keep utilizing AI tools in the future.	"I intend to continue using AI platforms".

C. Validation Techniques

The systematic item reduction and validation process is shown in Table 3. The original version was a 55-item borrowed and adapted version of existing constructs, where interviews, Content Validity (CVR), Q-sorting, pre-test and pilot testing were performed at each of the successive stages to guarantee clarity, relevance and psychometric soundness. Problematic or redundant items were removed at every step and the final validated scale included 21 items that suggested satisfactory reliability and construct validity.

Table 3. Timeline of item reduction and validation process

Stage	Process	Action Taken
Initial Pool	Adapted from literature (usefulness, trust, satisfaction, privacy, system quality, continuance intention)	Starting point
Interviews	Expert interviews (3 professors)	Removed 24 items
Content Evaluation Panel	CVR with 3 experts (threshold = 0.99)	5 items removed (CVR < 1.00)
Q-Sorting	Specialists sorted items into constructs; Cohen's Kappa was applied	3 items removed (Kappa < 0.7)
Pre-Test	23 respondents reviewed clarity and usability	2 items removed
Pilot Test	504 participants tested the reliability and validity	No further removal

1) Interviews (face validity)

This process was aimed at showing that every survey item was an effective and accurate measure of constructs such as perceived usefulness, trust, satisfaction, privacy concern, or other variables that could measure the adoption of Generative AI tools in educational institutions. The interview process ensured that the items were suitable, clear and relevant to the context of those to whom they were presented. To do that, three experts were chosen as all of them are professors and have a background in Generative AI and are also actively involved in the education sector. These experts were involved in structured interviews using a questionnaire consisting of 55 items that were adapted from validated constructs such as satisfaction, trust, perceived usefulness, and privacy concern. They were requested to rate the items for clarity, relevance, and context. The validation process had two steps of item refinement. In the first review, the experts identified five items which were unclear or redundant, two of which were deleted and three items revised, leaving 53 items. The work done on the refined items in the second review was done with theoretical precision and re-evaluated by the experts for conceptual congruence with the constructs intended. This was a systematic process that increased the validity and appropriateness of the survey tool.

- **Relevance and clarity:** Checked whether each item represents its underlying construct and whether the wording was accurate and appropriate.
- **Understandability:** Items should be straightforward, using vocabulary that target students and faculty are familiar with.
- **Alignment with Constructs:** An item should best fit logically into the construct it was assigned to without unnecessarily overlapping with other constructs.

The experts' feedback was then compiled to systematically evaluate areas needing revision. Items that more than one expert deemed substantially unclear or redundant were either rewritten or removed. This process led to the removal of 22 items, leaving 31 for the next phase.

2) Content evaluation panel (content validity)

To ensure content validity, experts from academia or industry with expertise in digital technologies or AI in education were invited. They examined a detailed list of 31 items related to the constructs of perceived usefulness, perceived trust, system quality, and satisfaction. The expert panel was then asked to rate the items in regard to their content relevance and clarity as essential, useful, but not essential or unnecessary. In order to measure the results, the Content CVR was computed with the help of the formula developed by Lawshe [29]:

$$CVR = (ne - N/2)/(N/2)$$

where *ne* is the number of experts rating the item as essential, and *N* is the total number of experts.

- For 3 experts, the minimum acceptable CVR is 0.99.
- Only items rated essential by all three experts (CVR = 1.00) were retained.
- If 2 out of 3 experts rated an item essential, CVR = 0.33.
- (below the threshold), and the item was revised or removed.

Outcome: Based on CVR results, five items were removed, reducing the list from 31 to 26 items.

The evaluation of AI services based on CVR scores is presented in Table 4.

Table 4. Evaluation of AI services based on CVR scores

Item	(Essential)	Score	Decision
"Using AI services improves access".	3 out of 3	1.00	Retain
"The system quality of AI tools is high".	3 out of 3	1.00	Retain
"I trust AI to manage my personal data".	2 out of 3	0.33	Revise or remove

3) Q-sorting (discriminant and convergent validity)

A systematic procedure was followed in order to test the correlation of items belonging to the same construct and to be different to items of different constructs. First, three specialists in the field of educational technology with knowledge of AI were invited to participate. A Q-sorting exercise was then carried out, in which the remaining 26 items appeared without their construct labels, and the judges were requested to sort them into the pre-established categories. The analysis of the results was carried out by computing the hit ratio and by using Cohen Kappa to determine inter-rater reliability. Cohen's Kappa is a statistical measure that evaluates the degree of agreement between assessors beyond what would be expected by chance, providing a more accurate assessment of inter-rater reliability than simple percentage agreement, particularly for categorical data [30]. Items with an agreement value below 0.7 were considered for revision. Based on this analysis, three items were removed due to poor alignment (Cohen's Kappa < 0.7), while two items were refined for clarity and accuracy. This process resulted in a finalized set of 23 items for further testing.

4) Pre-test

Table 5. Survey questions assessing factors influencing the continuance use of generative AI tools in education

Construct	Survey Items
PU (Perceived Usefulness)	• Employing Generative AI tools increases my efficiency in tasks of an educational nature. • These Generative AI tools help me gain productivity when doing work. • It can also be said that Generative AI tools are helpful to me in my educational activities.
IQ (Information Quality)	• AI tools produce relevant content that I need to apply in my situation. • When dealing with Generative AI tools, the results yielded by such programs are often reliable and consistent with my expectations. • The Generative AI tools come hand in hand with timely help as may be required from time to time.
PC (Privacy Concerns)	• I am concerned that Generative AI tools may collect more personal data than necessary. • I worry that my personal or academic information could be misused when using Generative AI tools. • I am concerned about how my data is stored, shared, or used by Generative AI tools.
SyQ (System Quality)	• The Generative AI tools are easy to use and are available to everyone. • Generative AI tools are visually and functionally appealing to users. • Generative AI tools are stable and efficient, maintaining performance even when processing complex or high-volume tasks.
S (Satisfaction)	• The experience of using Generative AI tools for educational purposes is quite satisfactory. • I found that using AI for educational purposes is exciting. • I am pleased with my overall experience of Generative AI.
T (Trust)	• I believe Generative AI tools do not violate my privacy of personal and academic data. • I am confident that Generative AI tools will prove themselves over time to be reliable. • I trust Generative AI tools to provide reliable and unbiased outputs in educational contexts.
CI (Continuance Intention)	• I intend to use Generative AI tools in my educational activities. • I intend to keep using Generative AI tools in the future. • If possible, I would continue using Generative AI tools over other alternatives.

Note: Respondents rated each item on a 5-point Likert scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

The purpose is to check, in an advanced stage, the clarity, reliability, and usability of the survey items for wider dissemination. Table 5 presents the survey questions assessing factors influencing the continuance use of Generative AI.

A small-scale pre-test was conducted with 23 respondents to assess question clarity and survey length and identify potential sources of confusion (Table 6). Two items were removed, leaving 21 items.

Table 6. Pre-test and pilot-test reliability results

Construct	Cronbach's Alpha (Pre-test)	Cronbach's Alpha (Pilot-test)	Final Number of Items
PU	0.78	0.82	3
IQ	0.80	0.80	3
SyQ	0.69	0.73	3
PC	0.73	0.79	3
T	0.72	0.78	3
S	0.80	0.84	3
CI	0.74	0.79	3

The pre-test and pilot-test reliability findings were used to make final decisions regarding item retention before full-scale validation in Table 6. It is observed that pre-test Cronbach's alpha of System Quality (SyQ = 0.69) slightly dropped below the traditional level of 0.70. This can be explained by the limited pre-test sample size (n = 23), which can yield unstable estimates with very small samples. The SyQ items, in turn, were revised to be clear and contextually accurate prior to the pilot test, and then the alpha rose to 0.73, which validated that the construct met the desired reliability in the full-scale validation.

D. Data Collection

The validated questionnaire was administered to 504 participants who were recruited from public universities which offered undergraduate and postgraduate programs that used Generative AI tools for their academic work, as presented in Table 7. The sampling frame was constructed using institutional enrollment and faculty directories obtained through departmental coordination. The researchers used stratified random sampling to achieve proportional representation of essential demographic categories, which included gender, age group, education level and occupation. The study used systematic random sampling to choose participants from each stratum by selecting individuals at fixed intervals from the structured sampling system. The study used Google Forms for electronic survey distribution, which required participants to have prior experience with Generative AI tools because the research focused on their intention to continue using the technology. The purpose of the study and confidentiality of the answers were explained to all participants prior to their participation.

Table 7. Demographic characteristics of respondents

Demographic Characteristic	Frequency	Percentage
Gender (Male / Female)	258 / 246	51.2% / 48.8%
Age Group (18–25 / 26–35 / 36+)	210 / 185 / 109	41.7% / 36.7% / 21.6%
Education Level (Bachelor's / Master's / PhD)	240 / 190 / 74	47.6% / 37.7% / 14.7%
Occupation (Student / Faculty)	283 / 221	56.2% / 43.8%

E. Data Analysis

Data analysis was conducted through the Statistical Package for the Social Sciences (SPSS). The steps undertaken are summarized below:

Reliability Testing: Internal consistency-reliability for the items for each construct is measured using Cronbach's alpha.

Exploratory Factor Analysis (EFA): It was used to test the underlying factors structure of the measurement instrument. EFA was selected because it serves better in scale development since it aims at the identification of latent constructs, in that it distinguishes common variance and unique and error variance [31, 32]. The extraction method used was Principal Axis Factoring (PAF) since it is strong with data measured on Likert scales, which do not necessarily meet the multivariate normality requirements. Direct Oblimin rotation (delta = 0) was used to allow the factors to be correlated, as the theoretical constructs in the proposed framework, such as perceived usefulness, trust, privacy concerns, and satisfaction, are conceptually correlated. Items with factor loadings below 0.50 or with high cross-loadings were considered for removal.

Sampling Adequacy Tests: The appropriateness of data was tested with the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett Test of Sphericity before the extraction of the factors. The KMO value of 0.812, as given in Table 8, is higher than the recommended level of 0.70, so the sample was sufficient to analyze the factors. The Test of Sphericity by Bartlett was significant (χ^2 = 1245.36, p < 0.001), which proved that the correlation matrix had enough relationships between variables to continue with the factor extraction.

Table 8. Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity

Test	Value	Threshold	Result
Kaiser-Meyer-Olkin (KMO)	0.812	>0.70	Adequate
Bartlett's Test of Sphericity	1245.36	<0.001	Significant

Factor Structure: The number of factors was determined based on theoretical expectations derived from the proposed seven-construct framework, which was further supported by the established item structure confirmed through the systematic instrument development process. As reported in Table 9, all constructs demonstrated factor loading ranges exceeding the recommended threshold of 0.50, with values ranging from 0.67 to 0.81 across all seven constructs. Cross-loading examination confirmed that each item loaded substantially higher on its intended construct than on any other, providing evidence of structural validity.

Table 9. Construct reliability and convergent validity

Construct	Factor Loading Range	Cronbach's Alpha	Composite Reliability (CR)	AVE
PU	0.74–0.81	0.82	0.85	0.61
IQ	0.72–0.79	0.83	0.86	0.62
SyQ	0.71–0.76	0.81	0.84	0.59
PC	0.69–0.74	0.79	0.83	0.55
T	0.67–0.72	0.77	0.80	0.51
S	0.75–0.80	0.84	0.88	0.64
CI	0.73–0.79	0.81	0.84	0.57

Convergent Validity and Composite Reliability: According to Table 9, all the factor loading ranges were greater than the recommended threshold of 0.50, CR values were between 0.80 (Trust) and 0.88 (Satisfaction), and AVE values were between 0.51 (Trust) and 0.64 (Satisfaction), which exceeded the recommended thresholds of 0.50. These findings, and the alpha values of Cronbach's which are between 0.77 and 0.84 support the reliability and convergent validity of the measuring instrument.

Discriminant Validity: Discriminant validity was assessed using two complementary approaches: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. As presented in Table 10, the square root of AVE for each construct exceeded its correlations with all other constructs, satisfying the Fornell-Larcker criterion. Furthermore, as shown in Table 11, all HTMT values remained below the conservative threshold of 0.85, providing additional confirmation of discriminant validity. The comparison among factors loading, Cronbach's Alpha, and composite reliability is shown in Fig. 2.

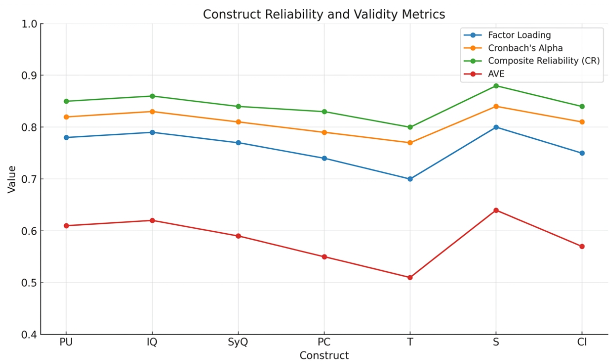

Fig. 2. Comparison of factor loading, Cronbach's Alpha, and composite reliability.

Table 10. Fornell-Larcker criterion

Construct	PU	IQ	SyQ	PC	T	S	CI
PU	0.78						
IQ	0.55	0.78					
SyQ	0.52	0.53	0.76				
PC	0.48	0.5	0.49	0.74			
T	0.5	0.47	0.46	0.44	0.71		
S	0.57	0.56	0.55	0.52	0.5	0.80	
CI	0.54	0.52	0.51	0.49	0.48	0.53	0.75

Table 11. HTMT ratios

Construct Pair	HTMT Value	Threshold	Result
PU–IQ	0.68	<0.85	Valid
PU–SyQ	0.65	<0.85	Valid
PU–PC	0.6	<0.85	Valid
PU–T	0.62	<0.85	Valid
PU–S	0.7	<0.85	Valid
PU–CI	0.66	<0.85	Valid
IQ–SyQ	0.64	<0.85	Valid
IQ–PC	0.59	<0.85	Valid
IQ–T	0.61	<0.85	Valid
IQ–S	0.72	<0.85	Valid
IQ–CI	0.67	<0.85	Valid
SyQ–PC	0.63	<0.85	Valid
SyQ–T	0.58	<0.85	Valid
SyQ–S	0.69	<0.85	Valid
SyQ–CI	0.65	<0.85	Valid
PC–T	0.6	<0.85	Valid
PC–S	0.68	<0.85	Valid
PC–CI	0.64	<0.85	Valid
T–S	0.71	<0.85	Valid
T–CI	0.66	<0.85	Valid
S–CI	0.74	<0.85	Valid

The factor correlation matrix derived from the oblique rotation solution is presented in Table 12, further confirming the moderate inter-construct correlations that justify the use of Direct Oblimin rotation

Table 12. Factor correlation matrix (oblique rotation)

Construct	PU	IQ	SyQ	PC	T	S	CI
PU	1.00						
IQ	0.55	1.00					
SyQ	0.52	0.53	1.00				
PC	0.48	0.50	0.49	1.00			
T	0.50	0.47	0.46	0.44	1.00		
S	0.57	0.56	0.55	0.52	0.50	1.00	
CI	0.54	0.52	0.51	0.49	0.48	0.53	1.00

Cross-Loadings: A cross-loading matrix established that every item loaded highly on its intended construct of interest as compared to any other construct, which further supports the fact that there was discriminant validity.

IV. Discussion

The present study focused on the development and validation of a measurement instrument to assess factors influencing users' continuance intention toward Generative AI tools in educational settings. As in previous instrument-development studies, the discussion focuses on assessment of psychometric properties instead of causal relationships. The study established the reliability and validity of a finalized scale consisting of 21 items over seven constructs based on the IS Success Model, the ECM and external factors like privacy concerns and trust. This validated instrument is used to offer a system and consistent method for future research on the use of Generative AI within the education sector.

The results of this empirical study show high internal consistency and high convergent validity for all constructs. The Cronbach alpha coefficient for each instrument ranged between 0.77 (Trust) and 0.84 (Satisfaction) which is greater than the threshold of 0.70 as indicated in Table 9. The Composite Reliability values ranged from 0.80 to 0.88 with the AVE values between 0.51 and 0.64, which meet the requirements of validity. Other constructs such as Perceived Usefulness ($\alpha = 0.82$, AVE = 0.61), System Quality ($\alpha = 0.81$, AVE = 0.59) also demonstrated strong reliability, and confirming their relevance for assessing continued engagement with AI tools. The findings are also aligned with the post-adoption findings in the studies based on the ECM that also identified satisfaction and perceived usefulness as strong predictors of continued use of ChatGPT by students [23]. It is observed that Satisfaction has a high psychometric reliability, with $\alpha = 0.84$ and AVE = 0.64, which aligns with the theoretical centrality of this construct as the primary post-adoption construct in the Generative AI education scenario, as predicted by the ECM, which suggests that satisfaction should mediate the relationship between confirmation and continuance intention.

To establish discriminant validity, complementary analyses were also conducted. All the square root of the AVE for each construct are larger than the inter-construct correlation values in Table 10, and all the HTMT ratios of constructs pairs are lower than the critical value of 0.85 in Table 11. The results show that all seven constructs are conceptually distinct dimensions of continuance intention. The discriminant validity checks conducted in the current study have been largely absent from existing studies on generative-AI adoption, which rely on current TAM or UTAUT2 scales without systematic item reduction or HTMT tests [18, 21]. Theoretically, this distinction matters because the instruments created directly from TAM or UTAUT2 without domain-specific validation might not measure constructs specific to the context of Generative AI, such as Privacy Concerns and Trust, which are not measured in traditional adoption models. To address this, the current instrument explicitly operationalizes these constructs as psychometrically distinct dimensions, thereby expanding the existing measurement base that can be used by researchers conducting research on AI adoption.

The reliability scores for Trust (α = 0.77) and Privacy Concerns (α = 0.55) highlight the significance of these ethical and security-related constructs in AI-based learning environments. These results align with previous studies on data protection, system reliability, and responsible AI use [6, 13]. Furthermore, the conceptual placement of Satisfaction (α = 0.84, AVE = 0.64) as a new post-adoption construct that connects performance-related qualities to Continuance Intention (α = 0.81, AVE = 0.57) extends the ECM findings to the world of generative-AI. Relatively lower reliability of Trust in comparison with other constructs can be explained theoretically instead of being a psychometric weakness. Trust in AI systems involves cognitive evaluations of system reliability, affective beliefs about data security, and normative beliefs about responsible use of AI systems and is thus more complex to measure using a small set of items. Future studies can be enhanced by creating a more detailed Trust subscale that identifies three factors: cognitive trust (system reliability tests), affective trust (beliefs regarding data security), and normative trust (perceptions regarding responsible AI conduct). Such a distinction would enhance the accuracy of measurement and give constructive feedback on how to refine the instrument.

The validated instrument has significant implications for educational policy and practice. System Quality demonstrates strong psychometric properties (α = 0.81, AVE = 0.59), meaning users consistently evaluate usability and reliability of AI platforms. Therefore, institutions should prioritize platform performance and accessibility when implementing Generative AI tools. The high Privacy Concerns (α = 0.79, AVE = 0.55) indicate that students and faculty consistently consider data security when using these tools, highlighting the need for transparent institutional data governance policies to enhance long-term adoption. For EdTech developers, the strong reliability of the Satisfaction construct indicates that user experience design must be considered as one of the key motivators of long-term engagement. This instrument can be used by policymakers to implement systematic cross-institutional analysis of the adoption of Generative AI, enabling evidence-based judgments on the use of AI in national education systems.

Overall, this discussion indicates that this study is methodologically valuable as it represents a well-founded domain-specific scale of continuance intention with respect to Generative AI tools in education. This study, not like other studies that have examined the structural relationships through adapted measurement scales, developed a validated measurement basis [19, 20]. This study developed a validated measurement basis. This instrument enables future studies to test causal pathways, mediating effects, and cross-cultural applicability with greater empirical precision.

V. Conclusion

The study designed and pilot-tested a tool to assess the constructs that were found to impact sustained usage intention for Generative AI technologies in education. Based on the constructs of perceived usefulness, trust, system quality and satisfaction, this research demonstrates that there are crucial drivers that can substantially enhance user engagement and retention in digital educational services. Internal consistency was determined using statistical reliability tests including Cronbach's alpha.

This study introduced a validated tool that could be used in future research to capture the influencing factors of the continuance intention of the Generative AI tools in the education sector. The study focused on the transformative changes in integrating Generative AI toward accessible and interactive digital learning environments. The findings of this study offer a basis for future research into the effects of AI tools on student performance, cultural variations in the use of technology, and comparative analysis of the various technological efforts. Addressing these gaps will further refine the framework and encourage the sustained refined use of Generative AI tools to support and enhance learning across a variety of settings.

Overall, the present research contributes to the existing knowledge on digital education and offers an understanding of what motivates the use and long-term use of Generative AI tools. Overall, the study represents an initial step towards methodologically defining and validating constructs that will allow for further investigation of the continuance intention of Generative AI tools in teaching. The outcomes are part of a broader conversation and provide fresh insights into the field of research and innovation in this field of rapid development. One of the recommendations from this study is that the designed and tested questionnaire should be applied on future studies with larger and diversified sample to test the magnitude and significance of each factor. The validated questionnaire can now offer a more consistent perspective and reinforce the framework to allow an increasingly specific set of interventions and policymaking. With the ongoing projects and initiatives, the future of Generative AI in education holds promising potential for supporting diverse learning requirements across the evolving educational landscape.

Conflict of Interest

The author declares no conflict of interest.

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