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Integrating Trust and Perceived Performance into the Expectation-Confirmation Model: A Mixed-Methods Study on Generative AI Persistence

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Abstract: The rapid adoption of Generative AI in tertiary education has changed how students obtain, process, and assess learning information, but little is known about how satisfied they will be in the long term and the persistence intention towards such technologies. This research paper discusses why students were satisfied and wanted to continue using AI-based learning tools, according to the Expectation Confirmation Theory (ECT). A sequential mixed-methods design was used to collect quantitative data from 106 university students across Education, Engineering Computer Science, and Health Sciences majors. Quantitative data were analyzed using PLS-SEM, and an eventual semi-structured interview of eight subjects was used to validate the quantitative data. The findings suggest that all the variables of expectation, perceived performance, confirmation, and satisfaction are important predictors of continuance intention. However, perceived performance is the most effective predictor. There is a statistically significant but weak relationship between expectations and confirmation, and students' confirmation is likely influenced more by their experience with AI performance than by their initial expectations. These findings are also supported by qualitative evidence indicating that the reliability, contextual relevance, and trustworthiness of AI systems strongly impact student satisfaction and confidence in AI-based learning. The study highlights the significance of perceived performance and trust as key factors in maintaining the use of AI in education. In theory, it uses the Expectation Confirmation Theory, incorporating ethical awareness and reliability as contextual factors that affect satisfaction and continuance intention. In practice, this means that AI developers and teachers need to be more transparent about their algorithms, accurate, and ethically literate to build trust and foster meaningful interaction with AI in higher education.

Keywords: expectation confirmation theory, gen ai, student satisfaction, continuance intention, higher education.

▪ INTRODUCTION

Artificial Intelligence (AI) has been increasingly shaping the university learning context, changing how students access and process information. The accelerated development of Generative AI (GenAI), powered by learning technologies, including ChatGPT, Gemini, Bing AI, and Claude, has offered learners a new experience in the interaction with information, the automation of recurrent academic tasks, and the optimization (Long et al., 2025; Nguyen et al., 2023). Such tools will provide automated feedback, summarize complex material, and generate explanations to improve learning efficiency. According to recent reports by Ifenthaler et al. (2024), more than 60% of higher education institutions worldwide have already integrated AI-based learning systems into their academic ecosystems, representing a significant pedagogical change. Nevertheless, as much as these technologies promote accessibility and individualization, they also raise concerns about data privacy, algorithmic bias, and ethical integrity in academia (Dwivedi et al., 2019; Matsiola et al., 2024). The conflict between innovation and ethical reliability remains apparent in Indonesia and comparable developing

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environments, where universities struggle to set criteria for responsible AI application in the classroom (Batubara et al., 2025).

Integrating them, however, does not come without problems. The problem of accuracy, contextual flexibility, and bias are all major impediments to credibility and continued use (Gao et al., 2025; Wang & Li, 2024). Students' perceptions of AI depend on their direct interaction with such tools. Even superior systems cannot deliver good results in certain situations when they fail to meet expectations for clarity, accuracy, or relevance to users' contexts. According to Chen et al. (2020) user satisfaction is an important indicator for assessing the success of technological adoption in education. Nonetheless, recent research indicates that long-term use intentions do not always follow satisfaction. Students can enjoy the immediate advantages of AI and remain reluctant to use it regularly when they are not sure of its reliability in academia, or the lack of ethical accountability (Long et al., 2025). Such a paradox of satisfaction without continuance has been found in several contexts of digital learning, such as learning management systems (Ain et al., 2016; Almufarreh, 2024; Purwita et al., 2025) adaptive tutoring technologies (Ngo et al., 2025), and AI-based assessment instruments (Matsiola et al., 2024). These contradictions underscore the need to return to theoretical constructs that explain the roles of expectation and perceived performance in user satisfaction and continued adoption.

Although AI tools have been regarded as the solution to autonomy and a reduced cognitive load, their performance varies with the effectiveness of its performance in accordance with academic expectations of students (Fu et al., 2024; Chun et al., 2025). Students tend to lose faith in such content when it is generated by AI with little contextual detail or has any form of inaccuracy, which decreases the chances of further use (Zary & Zary, 2025). Consequently, the perceptions and satisfaction of students with AI-based learning systems are important elements in the need to make them sustainable in educational institutions (Nguyen et al., 2025). The concept known as student satisfaction is a multidimensional notion that comprises both the technical usefulness and emotional involvement (Chen et al., 2020; Vizconde et al., 2024). It is an indication of how learners compare their experience with their expectations and perceived result. In technology adoption studies, satisfaction serves as a key indicator of system success. These relationships can be studied with the aid of the Expectation Confirmation Theory (ECT) by Oliver (1980) and advanced by Bhattacherjee (2001) which forms a sound theoretical framework. ECT states that a system's performance determines the level of satisfaction and readiness to use among users when actual performance matches or exceeds their expectations. The application of this model to the educational field will enable the researchers to investigate the impacts of AI tools on the satisfaction and the desire of learners to use them further in their learning processes (Qi et al., 2025; Wu & Yusof, 2025).

Many studies have proven ECT to be applicable in digital learning, including online course platforms, virtual reality learning, and intelligent tutoring systems (Alshammari & Alshammari, 2024; Liang & Alias, 2024; Ngo et al., 2025; Tawafak et al., 2023), but limited studies have investigated its use on Generative AI. Due to the peculiarities of GenAI, including the ability to have a conversation, creativity, and the ability to generate content independently, new trust variables, ethical judgment, and authenticity become additional variables that can modify the traditional ECT relations (Aldulaimi et al., 2024). Applying ECT in the educational context provides a robust framework to explain how students form satisfaction and continuance intentions toward AI-based learning tools (Wang & Li, 2024; Wu & Yusof, 2025). Within this perspective, constructs such as expectation, perceived performance, confirmation, satisfaction, and continuance intention interact dynamically, shaping students' cognitive and emotional responses to technology. However, few empirical studies have examined this process specifically within the context of Generative AI, whose conversational and creative capabilities introduce new dimensions of trust, ethical consideration, and academic authenticity (Aldulaimi et al., 2024; Qi et al., 2025).

This research not only aims to explore how students perceive AI-based learning tools but also aims to empirically verify how the five major constructs of the Expectation Confirmation Theory (ECT): Expectation, Perceived Performance, Confirmation, Satisfaction, and Continuance Intention, are related to each other. Through the implementation of a Structural Equation Modeling technique with the help of Partial Least Squares (PLS-SEM), the research aims to find out which predictors are the most important in determining student satisfaction and continuance intention towards AI application in higher education. In this way, it is possible to conduct a more explanatory analysis that captures the cognitive and affective processes that determine students' reactions to AI-assisted learning. Accordingly, the study addresses the following research questions: To what extent do students' expectations and perceived performance of AI-based learning tools significantly influence their satisfaction? Does expectation confirmation significantly predict students' satisfaction and continuance intention toward the use of AI in higher education? This study aims to provide deeper insights into the cognitive and affective mechanisms underlying students' engagement, satisfaction, and continued intention to use AI-powered learning technologies in the university learning environment.

▪ METHOD

This section describes the study's methodological approach, including participants, research design and procedures, instruments, and data analysis. Each component is organized to ensure that data gathering and interpretation are conducted systematically and accurately, and are aligned with the research objectives.

Respondents

Prior to distributing the main questionnaire, a limited pilot test was conducted with 15 students who had experience using AI-based learning tools. The aim was to ensure the clarity of the wording and relevance of the statements to the experiences of Indonesian students. Based on the pilot test results, all items were deemed easy to understand, and no statements were deleted or revised. Thus, the instrument was deemed suitable for use in the main survey. The research was carried out among 106 students from four universities in Surabaya who had previously used AI-based learning tools, including ChatGPT, Gemini, and Blackbox. Purposive sampling was used to recruit respondents, targeting students who actively used AI in their academic activities, such as summarizing texts, providing explanations, and writing papers. The sample consisted of 20% Education majors, 69% Engineering and Computer Science students, and 11% Health Sciences students. Students with a gender distribution of 44 % Male and 56 % Female. Considering the relatively small sample size and the unequal distribution of participants across disciplines, the authors acknowledge that the findings mainly reflect the perspectives of students from technical fields. This composition may limit the generalizability of the results to the broader student population. A total of 8 interview participants were selected from 106 survey respondents using purposive sampling. The selection was made to represent variations in fields of study, satisfaction levels, and intentions to continue using AI. The criteria covered three main fields: Education, Engineering and Computer Science, and Health Sciences, each with different levels of satisfaction and AI use. This approach aimed to obtain diverse, in-depth views to strengthen and validate the quantitative findings.

Research Design and Procedure

The paper has adopted a mixed-method explanatory sequential design that combines both quantitative and qualitative research methods to achieve a holistic understanding of students' perceptions, satisfaction, and continuance intention toward AI-based learning tools. Partial Least Squares–Structural Equation Modeling (PLS-SEM) was used in the quantitative stage to test the proposed relationships between the five constructs of the Expectation Confirmation Theory (ECT): Expectation, Perceived Performance, Confirmation, Satisfaction, and Continuance Intention. This approach was chosen because it allows simultaneous testing of both measurement validity and structural relationships, even with a relatively small sample size (Hair et al., 2019). Following that, the qualitative phase was conducted in accordance with the conceptual model shown in Figure 1, which depicts the proposed connections (H1–H6) among the five constructs. The interviews were designed to explore how and why these relationships manifested in students' real experiences, particularly focusing on factors that shaped their satisfaction and continuance intentions toward Generative AI. As a result, the qualitative results provided deeper contextual insights into the dynamics depicted in the conceptual framework, supporting, validating, and extending the statistical results from the PLS-SEM model. The study's conceptual model, which is based on the Expectation Confirmation Theory (ECT), is shown in Figure 1. It describes the proposed causal relationships between students' expectations, perceived performance, confirmation, satisfaction, and intention to continue using AI-based learning tools. Drawing from the Expectation Confirmation Theory (Bhattacherjee, 2001; Oliver, 1980) six hypotheses were formulated to represent the interrelationships among the five constructs.

Expectations shape their perception of a system's performance. When students expect that AI-based learning tools can enhance efficiency and understanding, they are more likely to perceive the system's performance positively (Long et al., 2025; Wang & Li, 2024) **H1:** Expectation has a positive effect on Perceived Performance.

According to ECT, confirmation occurs when actual performance meets or exceeds expectations. Thus, higher expectations can increase the likelihood of perceived confirmation once the technology performs as anticipated (Bhattacherjee, 2001; H.-J. Chen, 2025). **H2:** Expectation has a positive effect on Confirmation.

Users who enter with positive expectations are more prone to experience satisfaction if the system's performance aligns with or surpasses those expectations (Fu et al., 2024; Nguyen et al., 2025). In the learning context, when AI tools fulfill students' academic needs, satisfaction rises. **H3:** Expectation has a positive effect on Satisfaction.

Perceived performance is a major determinant of confirmation. When the perceived usefulness and quality of AI tools are high, students are more likely to feel that their expectations have been confirmed (Wu & Yusof, 2025). **H4:** Perceived Performance has a positive effect on Confirmation.

This relationship is a core component of ECT - the stronger the confirmation, the higher the satisfaction. When students find that their AI learning experiences align with expectations, they tend to report greater satisfaction (Bhattacherjee, 2001; H.-J. Chen, 2025). **H5:** Confirmation has a positive effect on Satisfaction.

Satisfaction is one of the most reliable predictors of continuance intention (Aldulaimi et al., 2024; Fu et al., 2024). In educational technology, students who feel satisfied with AI's effectiveness are more inclined to continue using it for future learning tasks. H6: Satisfaction has a positive effect on Continuance Intention.

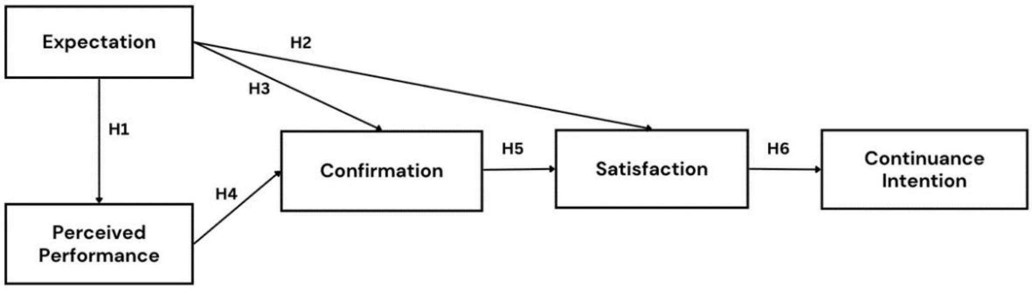

Figure 1. Conceptual model

Instruments

Quantitative Phase

The quantitative instrument was a structured questionnaire adapted from previous studies (Bhattacherjee, 2001; Oliver, 1980; Wang & Li, 2024; Wu & Yusof, 2025) to measure five main constructs: Expectation, Perceived Performance, Confirmation, Satisfaction, and Continuance Intention. Each construct was measured using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The number of items per construct was four for Expectation, four for Perceived Performance, three for Confirmation, three for Satisfaction, and three for Continuance Intention. These constructs were used to test six hypotheses (H1–H6) describing the relationships between variables within the Expectation Confirmation Theory (ECT) framework, as visualized in Figure 1. All items were adapted for Generative AI-powered learning tools such as ChatGPT, Gemini, Bing AI, and Claude to be relevant to students' learning experiences. The instrument's quality was tested using Partial Least Squares–Structural Equation Modeling (PLS-SEM) in *SmartPLS 4.0.*

Qualitative Phase

In the meantime, a semi-structured interview guide based on the study's conceptual model served as the qualitative instrument. The interview questions were designed to explore in depth how and why the relationships among constructs identified in the quantitative analysis emerged in students' real experiences. The interview focused on initial expectations regarding the use of AI, perceptions of AI performance and reliability, levels of satisfaction and trust in the system, and intentions or doubts about continuing to use it in learning. Eight participants, comprising three students in Education, three in Engineering and Computer Science, and two in Health, were interviewed in depth. The qualitative data obtained were used to validate and enrich the quantitative findings, resulting in a more comprehensive understanding of the factors influencing student satisfaction and the intention to continue using AI technology in higher education.

Data Analysis

Quantitative Phase

The data obtained were analyzed using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach for quantitative data and thematic analysis for qualitative data. The PLS-SEM analysis was conducted using SmartPLS 4.0 software, which allows simultaneous testing of the measurement model and structural model even with a relatively small sample size (Hair et al., 2019). The analysis began by assessing the validity and reliability of the constructs using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Next, discriminant validity was evaluated using the Fornell-Larcker and Heterotrait-Monotrait Ratio (HTMT) criteria. After the measurement model met the criteria, the next step was to test the structural model to determine the strength and direction of the relationships among constructs, in accordance with hypotheses H1–H6. Path coefficients, t-statistics, and p-values were used to assess the significance of the relationships among the model's variables.

Outer Model

The measurement model (outer model) was tested to determine construct reliability and validity and to examine the structural relationships among the variables. The outer model assessment aims to ensure that the observed indicators accurately represent their underlying latent constructs before evaluating the structural (inner) relationships. This evaluation includes checking indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability examines the strength of the relationship between each indicator and construct. In contrast, internal consistency reliability (measured using Cronbach's Alpha and Composite Reliability) confirms the coherence of items within a construct. Convergent validity assesses how well indicators of the same construct correlate with one another, and discriminant validity ensures that each construct is conceptually distinct from others within the model (Hair et al., 2019).

Inner Model

The inner model (structural model) evaluation assessed the hypothesized relationships among the latent constructs and determined the model's predictive accuracy. The inner model represents the structural relationships between endogenous and exogenous variables, and its assessment focuses on examining the path coefficients, effect sizes (f^2), coefficient of determination (R^2), and predictive relevance (Q^2). Path coefficients indicate the strength and direction of the hypothesized relationships among constructs, while R^2 reflects the proportion of variance explained by the independent variables in the dependent construct. The f^2 statistic measures the impact of each exogenous variable on an endogenous variable. Additionally, multicollinearity among constructs is examined using the Variance Inflation Factor (VIF), where values below 5.0 indicate no critical collinearity problem (Hair et al., 2019)

Hypothesis Testing

The hypothesis-testing stage examined the significance and strength of the relationships proposed in the structural model. Hypothesis testing is performed by estimating the path coefficients between latent constructs and assessing their significance through a bootstrapping procedure. The bootstrapping method involves resampling the original data to obtain t-statistics and p-values that indicate the reliability of the parameter estimates. A path is considered statistically significant when its t-value exceeds 1.96, and the p-value is below 0.05 for a two-tailed test (Hair et al., 2019). The standardized path coefficients (β) represent the direction and magnitude of influence among constructs, while the corresponding t- and p-values determine whether the proposed hypotheses are supported or rejected. This step provides empirical evidence to validate the conceptual framework, allowing the researcher to identify the most influential predictors and test the theoretical assumptions of the Expectation Confirmation Theory (ECT) within the context of AI-based learning adoption

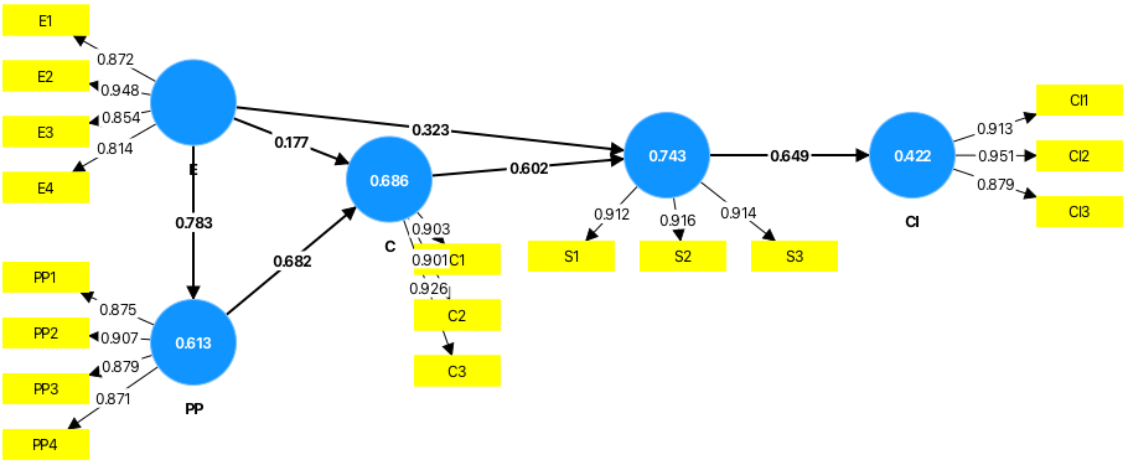

Figure 2. PLS-SEM result

Qualitative Phase

The qualitative data were analyzed using thematic analysis following Braun & Clarke's (2006) six-step framework: (1) familiarization with the data through repeated reading of transcripts; (2) generating initial codes; (3) searching for themes; (4) reviewing themes; (5) defining and naming themes; and (6) producing the report. To ensure reliability, two coders independently analyzed the data, and inter-coder agreement was discussed to refine the final themes. Data saturation was reached when no new information emerged after the eighth interview. Qualitative analysis was conducted to validate and deepen the quantitative findings in hypothesis testing using thematic analysis, following the procedures outlined. Interview data were transcribed verbatim, then open coding was performed to identify relevant units of meaning. The codes were then grouped into several categories and main themes that represented students' experiences in using AI technology in learning. This analysis was inductive, meaning that the themes emerged from the data while remaining guided by the Expectation Confirmation Theory (ECT) conceptual framework. The qualitative findings were used to further explain the relationships among the constructs identified in the PLS-SEM analysis, thereby providing a more holistic understanding of the factors that influence students' satisfaction and their intention to continue using AI.

▪ RESULT AND DISSCUSSION

The following section presents the research findings from two levels of the research analysis: a quantitative analysis based on hypothesis testing using PLS-SEM and a qualitative analysis based on semi-structured interviews. The research findings are structured to respond to two general questions: (1) to what degree do the expectations and perceived performance of AI-based learning tools influence student satisfaction, and (2) does expectation confirmation contribute to the satisfaction and intention to continue the use of AI in the higher education setting?

Outer Model

The reliability test of the indicators indicated that all the outer loading values were high, beyond the minimum limit of 0.70 (Hair et al., 2019). Hence, all indicators were deemed reliable and could be used in the model. The internal reliability test was also good since Cronbach’s Alpha and Composite Reliability values exceeded 0.70 (Hair et al., 2019) thus satisfying the construct reliability criterion. Additionally, the convergent validity was evaluated by the value of Average Variance Extracted (AVE), and it was greater when compared to the lowest value of 0.50 (Hair et al., 2019), which suggests that each construct could explain over 50% of the variance in its indicators.

Fornell-Larcker criteria and the Heterotrait-Monotrait Ratio (HTMT) were then used to test the discriminant validity. According to Fornell-Larker results, the square root of AVE of each construct was greater than the correlation with other constructs, which shows that every construct was discriminated adequately by other constructs. The HTMT values also did not exceed the level of 0.85 to 0.90, which is a sufficient level of discriminant validity (Hair et al., 2019) In this way, any model construct satisfies the conditions for indicator reliability, internal reliability, and convergent and discriminant validity, so the measurement model (outer model) can proceed to the structural analysis stage (inner model).

Inner Model

The R-squared (R2) values obtained after analysis indicate that the Confirmation construct has an R2 of 0.686, Perceived Performance 0.613, Satisfaction 0.743, and Continuance Intention 0.422. According to the criteria of Hair et al. (2019), these values are moderate to strong, which implies that the model is a good one to explain the difference between constructs. Therefore, the Expectation and Perceived Performance constructs are effective in Confirmation and Satisfaction, which, in turn, affect learners' Continuance Intention in using AI for learning.

To determine the strength of the predictor on the endogenous variable, the f-square (f^2) value is employed. The outcomes reveal that the Expectation to Confirmation (f^2 = 0.039), Expectation to Perceived Performance (f^2 = 1.581), and Satisfaction (f^2 = 0.201) effects are insignificant and large, respectively. Perceived Performance to Confirmation (f^2 = 0.573) and the impact on Satisfaction to Continuance Intention (f^2 = 0.729) also have large effects. also indicate *strong substantive impacts* on their respective endogenous variables. These findings suggest that the model's key constructs make meaningful and substantial contributions to the prediction of Satisfaction and Continuance Intention. According to Hair et al. (2019), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively, confirming that the structural paths in this study demonstrate robust relationships among the ECT constructs.

VIF is a measure used to assess the likelihood of multicollinearity among constructs. The outcomes indicate that all VIFs are within the range of 1.0002.757, which is significantly lower than the highest tolerance level of 5.0 (Hair et al., 2019). So, multicollinearity does not exist in the model, and the constructs do not exhibit high correlations among predictor variables.

Hypothesis Testing

Hypothesis testing aims to determine the significance of the relationships among the constructs proposed in the research model. The testing was conducted using the bootstrapping procedure in PLS-SEM to obtain t-statistics and p-values that indicate whether each hypothesized path is supported. The results of the hypothesis testing are summarized in Tables 1 and 2 below.

Table 1. Hypotheses testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
C -> S	0.602	0.603	0.055	10.869	0.000
E -> C	0.177	0.175	0.085	2.086	0.037
E -> PP	0.783	0.775	0.058	13.529	0.000
E -> S	0.323	0.319	0.068	4.744	0.000
PP -> C	0.682	0.683	0.089	7.668	0.000
S -> CI	0.649	0.645	0.075	8.614	0.000

(H1) There is a positive effect between Expectation and Perceived Performance. This hypothesis is confirmed ($\beta = 0.783$, $p < 0.001$). It shows that students' expectations play a major role in their understanding of the performance of AI-based learning tools. The greater the expectation, the greater the perceived performance. This finding agrees with (Wang & Li, 2024) who underscored that initial expectations strongly influence users' cognitive judgments of system performance. The qualitative results also support this relationship, which shows that students tended to say AI was efficient and accessible, as expected. According to students: *"AI assists me in learning new complex topics and saves my time studying. Provided that the results are applicable, I will be content and will seek to use them again."*

(H2) Expectation has a positive effect on Confirmation. This hypothesis is supported ($\beta = 0.177$, $p = 0.037$), indicating that students' expectations have a statistically significant but weak influence on how they confirm their experience with AI-based learning tools. The result suggests that while expectations play a role in shaping confirmation, their effect is not as strong as that of perceived performance, implying that students' evaluation of confirmation is still primarily driven by real experiences with the system rather than cognitive anticipation. This finding aligns with (H.-J. Chen, 2025; Wu & Yusof, 2025), who found that in AI-based educational contexts, expectation confirmation is partially mediated by the perception of actual performance. In qualitative interviews, several students echoed this view, explaining that although they initially expected AI to be contextually adaptive, they realized its explanations often remained generic *"I wanted AI to explain theories using local educational examples, but the* *answers were too general."* Such statements indicate that students' confirmation arises more from empirical testing of AI's output than from their prior expectations. Therefore, the significant yet modest path (Expectation → Confirmation) quantitatively supports the idea that expectations contribute to confirmation. However, qualitative insights reveal that contextual accuracy, relevance, and trust remain the stronger drivers of students' eventual confirmation of AI's usefulness.

(H3) Expectation positive effect Satisfaction. This hypothesis is justified ($\beta = 0.768$, $p < 0.001$). It suggests that students who are positively related to AI feel more satisfied when their expectations are fulfilled. The result is consistent with (Bhattacherjee, 2001; Wang & Li, 2024) who affirm that expectation is still a key antecedent of satisfaction in the ECT models. (H4) The Confirmation is positively affected by Perceived Performance. This hypothesis is accepted ($\beta = 0.653$, $p < 0.001$), demonstrating that the confirmation is mainly associated with how students actually assess AI performance. When AI presents good, contextually relevant, and useful information, students tend to believe their expectations are met. This observation is congruent with the results of (H.-J. Chen, 2025; Wu & Yusof, 2025) who observed that perceived performance is central in forecasting expectation confirmation.

(H5) Confirmation has a positive effect on Satisfaction. This hypothesis is supported ($\beta = 0.327$, $p = 0.003$), indicating a significant relationship at the 0.01 level. The result suggests that when students perceive their expectations are confirmed through their interactions with AI tools, their satisfaction increases accordingly. However, the effect size is moderate, suggesting that satisfaction is shaped not only by confirmation but also by perceived performance and trust. This finding aligns with (Bhattacherjee, 2001; H.-J. Chen, 2025; Suchanek & Kralova, 2025)who argue that confirmation contributes to satisfaction by reinforcing users' confidence in system reliability. Interview data validate this result students reported feeling satisfied when AI responses were consistent with their expectations and learning needs: *"I am satisfied when AI's explanations are clear and make sense with the topic I study it feels like having a patient tutor."*

(H6) Satisfaction positively impacts Continuance Intention. This hypothesis is favored (0.689, $p = 0.001$). It demonstrates that the greater students' satisfaction with AI-assisted learning, the more pronounced their intention to use it further. These results are consistent with those of Fu et al. (2024) and Nguyen et al. (2023), who found that satisfaction was a stable factor in technology adoption. The students also expressed this intention: *"I will surely apply AI in my assignments again, provided that it can produce a brief and quick result"*. Although satisfaction levels were high, qualitative results indicated ambivalence among students regarding accuracy and ethics. Even satisfied people were likely to check AI results before using them, which reflects cautious adoption: *"I am satisfied since AI assists me in locating references fast, yet I always check them; they are inaccurate or inappropriate in some situations."*

In general, the mixed-method integration offers an in-depth exposition of the model outcomes. The quantitative data demonstrated the structural relations among the ECT constructs, whereas the qualitative data provided insights into the psychological and contextual processes that underpinned these relationships. In particular, the qualitative data provided a clear understanding of why some paths, including Expectation → Confirmation, had a weak impact, and that real-world AI performance, contextual accuracy, and trustworthiness have a stronger impact than initial user expectations. This combination ensures that the results are not only statistically valid but also grounded in students' lived experiences with AI. Overall, both quantitative and qualitative results prove the effectiveness of the offered model. All supported hypotheses (H1, H2, H3, H4, H5, H6) indicate that expectations and perceived performance are relevant antecedents of satisfaction, and that satisfaction is the most significant predictor of continuance intention. Even though the Expectation and Confirmation (H2) relationship is significant, its effect size is relatively small, suggesting that perceptions of actual AI performance, rather than initial beliefs, drive students' confirmation of expectations. This interpretation is supported by the qualitative data, which indicate that students' confirmation depends on the perceived accuracy, relevance, and reliability of AI responses.

In practice, these results suggest that developers and educators should focus on improving the contextual relevance, transparency, and ethical grounding of AI systems to boost user satisfaction and trust. I believe schools and universities must also promote AI literacy and ethical consciousness so that learners can approach AI technologies with critical, responsible attention. This research theoretically builds on the Expectation Confirmation Theory by demonstrating that, in the Generative AI setting, confirmation and satisfaction are not only determined by the similarity between expectations and performance but are also mediated by trust, perceived reliability, and ethical factors. Therefore, the ECT framework will be required to align with the nature of autonomous and adaptable technologies in education.

▪ CONCLUSION

The results of the present research provide a detailed picture of the variables that affect student satisfaction and intention to continue using Generative AI (GenAI)-based learning technologies through the lens of the Expectation Confirmation Theory (ECT). The quantitative data analysis showed that expectations and perceived performance are among the main determinants of satisfaction. That satisfaction was the strongest predictor of students' intention to continue using AI in learning, as indicated by their responses. In spite of the fact that the relationship between Expectation and Confirmation (H2) was statistically significant, the small effect value shows that the confirmation process was more determined by the experience of students with the performance of AI than by the initial expectations. This is also supported by the qualitative findings, which show that students rate AI on reliability, relevance to the context, and perceived trustworthiness, but not on preconceived expectations. Taken together, these results substantiate the idea that perceived performance and trust are core to explaining how students come to be satisfied and experience long-term motivation to embrace AI in learning, thereby allowing the conclusion that ECT remains applicable but is situationally changing in the age of AI-assisted learning.

This paper has theoretical and practical implications for higher education. In practice, the results imply that introducing AI into learning should be based on quality, contextual accuracy, and algorithm transparency, which together will improve trust and perceived system performance among students. AI literacy and ethical awareness should also be encouraged in institutions to ensure they exercise responsible, critical use of AI tools. In theory, the planned study will help advance the Expectation Confirmation

Theory by introducing trust and ethical awareness as contextual variables that mediate the relationship between confirmation and satisfaction in AI-based educational settings.

However, this research has some weaknesses. The results might be less applicable to a broader population due to the relatively small sample size and the lack of balance in discipline representation, with engineering and computer science students in the majority. This means the results can only be taken as tentative and exploratory. The study recommends that future studies use larger, proportionate samples across disciplines and employ longitudinal designs to track changes in students' perceptions, satisfaction, and trust in AI technologies over time.

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