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GENERATIVE AI USE AMONG ACCOUNTING STUDENTS: QUALITY, SATISFACTION, PRIVACY CONCERNS, PERCEIVED RISKS, AND SOCIAL SUSTAINABILITY

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Abstract

Students' evaluations of generative AI and their perceptions of its risks relate to its use and perceived social impact. How sustainability in accounting education remains unclear. The study aims at examining these relationships using cross-sectional survey data from approximately 150 accounting students recruited through purposive sampling in Indonesia. Data were analyzed using partial least squares structural equation modeling (PLS-SEM). Service, system, and information quality were positively associated with user satisfaction. Perceived severity and susceptibility were positively associated with perceived threats. Satisfaction and perceived threats were positively associated with generative AI use, while privacy concerns showed no significant association with use. Generative AI use was positively associated with perceived social sustainability. The study integrates the DeLone and McLean Information Systems Success Model and Technology Threat Avoidance Theory, incorporating privacy concerns within a single model. The findings may inform guidance on responsible AI use that supports learning and upholds academic integrity.

INTRODUCTION

Over the past several decades, advances in machine learning, artificial intelligence (AI), and computer-assisted systems have expanded their applications across a wide range of fields. These technologies are increasingly employed to support decision-making processes and facilitate data analysis (Adamek & Solarz, 2025; Haldar et al., 2025). AI is understanded as a technology that include ability of computer system to do job that need human intelligent, like process nature language, solve problem, take decision, even make content with various shapes and methods, like rule-based system, machine learning, and deep learning, that each of them have different characteristic and difficulty (Muchlinski, 2022).

AI development has made Generative Artificial Intelligence (Generative AI) more integrated into daily life, including the education field (Al-Abdullatif, 2024; Banh & Strobel, 2023). Several examples of Generative AI, such as ChatGPT, Gemini, and Copilot have become part of student education, especially Generation Z. Because increase efficiency of procedure that already exist and open possibility of innovation on various field, Generative AI is viewed as breakthrough field of AI. Programming, translating, text summarization, business strategy, and even creation of promotional content have used this technology (Kanbach et al., 2024). This ability causes an increase in the adoption of Generative AI to improve innovation, productivity, and organizational efficiency (Al-Khatib, 2023). Generative AI implementation has social implication that complex even though this technology has many benefits especially for Gen Z, which is main group user of this technology. Gen Z tend to adopt technology base of AI quickly on activity like study, work, and communicate. Generative AI enables students to adjust their way of studying, get instant help for studying, and be more efficient in finishing school assignments. This study focuses on accounting education, where digital technologies are changing how students learn and apply accounting concepts. Alongside traditional bookkeeping, the field now involves data analytics, automated financial reporting, and support for strategic decision-making. Accounting students use generative AI for tasks such as analyzing financial statements, interpreting accounting standards like IFRS, developing audit scripts, and working through interactive case studies. These tasks require careful attention to accuracy, confidentiality, and professional skepticism, making accounting education a relevant setting for examining the adoption of generative AI (Ooi et al., 2025; Ratten, 2023).

The adoption of Generative AI in education raises several important issues, including academic integrity, data privacy, and excessive reliance on technological tools. Furthermore, disparities in AI literacy and access to digital infrastructure may create unequal opportunities for learners. These challenges suggest that the implications of Generative AI extend beyond technical considerations, encompassing broader questions of ethics, educational equity, and the long-term quality of education (Al-kfairy et al., 2024; Janumpally et al., 2024; Zhai et al., 2024).

Besides that, Generative AI also shifted paradigm of technology, from AI system that analyse to AI system is creative on academic field, this takes form as innovation of learning that more personal, interactive, adaptive, and automation various administration job that previously took learning time (Al-Qaysi et al., 2025). Nevertheless, innovation in this Generative AI must have correct governance so its use is clear and does not create social risks like data misuse, decline in critical thinking skills, digital literacy inequality, and so on (Al-kfairy et al., 2024; Janumpally et al., 2024; Zhai et al., 2024). In this context, Generative AI might help to reach social sustainability but also create social risk if not managed correctly (Liu et al., 2025; Tong, 2023). Many educational institutions in developing countries do not yet have policies or guidelines on Generative AI implementation in learning. Because of that, student use this technology without ethic guideline, academic limitation, or clear private protection (Ebikabowei, 2026).

Previous studies have examined generative AI in accounting education through students' perceptions, its ability to solve accounting cases, and its applications in learning and assessment (Cheng et al., 2024). These areas of inquiry provide a foundation for examining a further question: how do quality-related evaluations and threat perceptions relate to students' use of generative AI, and how is this use associated with perceived social sustainability? This question requires attention to both the

factors that encourage technology use and the concerns that may constrain it. In accounting education, these considerations are particularly relevant because students must evaluate information accuracy, exercise independent reasoning, and maintain academic integrity when using AI-generated content (Ballantine et al., 2024; Cheng et al., 2024). Accordingly, this study examines quality-related satisfaction and threat-related perceptions within a single framework and connects generative AI use to perceived social sustainability. Its intended contribution is an incremental explanation of technology use and its perceived social implications in accounting education.

To address this question, the study draws on the Information Systems Success Model and selected constructs from Technology Threat Avoidance Theory (TTAT). The Information Systems Success Model provides the basis for examining how service quality, system quality, and information quality relate to user satisfaction and, subsequently, generative AI use. TTAT provides a complementary perspective for examining perceived severity, perceived susceptibility, and perceived threats. Privacy concerns are included as a separate factor associated with use. Bringing these perspectives together allows the study to examine whether quality-related satisfaction and perceived threats each contribute to explaining generative AI use within the same model. The study further examines the association between use and perceived social sustainability, thereby connecting explanations of technology use with students' perceptions of its broader social implications in education. This framework represents a selective application and incremental extension of existing perspectives rather than a comprehensive test or substantial reformulation of either theory. Privacy concerns capture data-specific concerns, whereas perceived severity and perceived susceptibility represent assessments of the seriousness and likelihood of potential harm, respectively. In the proposed model, these two appraisals contribute to perceived threats, which relate to Generative AI use.

This study aims at examining how service quality, system quality, and information quality influence user satisfaction with the use of Generative AI in learning activities among accounting students. Service Quality as quality that is accepted by information system user from information system department or personal IT support, in this research could be explained as support that given by service provider, so that Generative AI could fulfil its purpose and give satisfaction for Generation Z as the user (Ngo et al., 2025). Service quality has components such as responsiveness, assurance, and empathy (Kondybayeva et al., 2024). Generative AI demonstrates high service quality when it is accessible whenever users need it, provides prompt responses, offers sufficient knowledge to support users' needs, and adapts its responses to individual characteristics and preferences. If Generative AI has high service quality, then its user satisfaction would also increase (AbdelKader & Sayed, 2022). Drawing on these arguments, this study proposes that higher service quality is associated with greater user satisfaction with generative AI in learning activities (H1).

System Quality is a characteristic that is expected from an information system, where it refers to how well Generative AI performs its function or how well Generative AI fulfils expected characteristics (Yu et al., 2025). (Almaiah et al., 2022) recommended system quality measurement based on ease of learning, ease of use, availability, response time, system reliability, flexibility, personalizability, system interactivity, and system security. Generative AI is considered to fulfil system quality if it is easy to learn and use (user-friendly), available when needed and could gave respond in quick time, could adapt to preference of user needs that diverse, could be reliable for fulfil user needs, interactive, and has system security. If Generative AI could show high system quality, satisfaction level also would increase (Wei et al., 2022). Drawing on these arguments, this study proposes that higher system quality is associated with greater user satisfaction with generative AI in learning activities (H2).

Information Quality refers to characteristics that are expected from output. Information quality on this research refers to output characteristic that produce by Generative AI where information quality measurement is base of relevance, usefulness, understandability, accuracy, reliability, currency, completeness, and timeliness(Alfaki, 2021). Generative AI is considered to meet the requirement of information quality if Generative AI could produce information that is relevant, useful, easy to understand, accurate, reliable, up-to-date, and available at needed time. If Generative AI could produce high-quality information so satisfaction level of user will be increased (Sayaf, 2023). Based on these

arguments, this study proposes that higher information quality is associated with greater user satisfaction with generative AI in learning activities (H3).

According to Al-Emran et al. (2025), user satisfaction is how far user expectations and needs could be fulfilled. User Satisfaction in this research refers to Generative AI ability to fulfil needs or expectation from user. If user needs could be fulfilled or expectations exceeded, that means a high level of user satisfaction. But if user needs couldn't be fulfilled or were below user expectations, that means a low level of user satisfaction. A high level of satisfaction will push users to use Generative AI and utilize it in daily life. Based on these arguments, this study proposes that greater user satisfaction is associated with increased use of generative AI in learning activities (H4).

Moreover, this study also analyses the influence of Perceived Severity and Perceived Susceptibility to perceived Threats then Perceived Threats to Generative AI use that finally analyse Generative AI use to Social Sustainability in education context. Al-Emran et al. (2025) conveyed that privacy concerns are generally tied to individual anxiety about gathering, saving, and using data. Anxiety of Generative AI users is generally related to the presence of unauthorized access, misuse of personal information, or the potential to lose control over that data. Some services require users to reveal personal data to get adjusted service with user characteristics. Data privacy right now had become significant issues and could affect acceptation to AI technology. If users have privacy concerns about Generative AI, then it could create doubt about Generative AI use. Based on these arguments, this study proposes that greater privacy concerns are associated with reduced use of generative AI in learning activities (H5).

Perceived severity is one of variable in TTAT (Technology Threat Avoidance Theory) that refers to level of severity or impact that felt by the threat certain ideology. Research by Session & Muller (2022) examined how far a cybersecurity professional views the level of severity that could be caused by a cyber threat to the system that they protect. The result of this research is perceived severity in significant affect perceived threat and next its effect motivation to avoid those threat. Based on these arguments, this study proposes that greater perceived severity is associated with higher perceived threats related to the use of generative AI in learning activities (H6).

Perceived Susceptibility refers to how far someone feels the risk of certain threats. In the context of cybersecurity in research from Session & Muller (2022), perceived susceptibility is the level of faith a cybersecurity professional has that the system they manage is at risk of a cyberattack. In this research, perceived susceptibility affects perceived threat: the higher the level of vulnerability felt by a cybersecurity professional to certain threats, the higher their perception of the level of those threats, which then affects the motivation to avoid threats and share information about cybersecurity. Based on these arguments, this study proposes that greater perceived susceptibility is associated with higher perceived threats related to the use of generative AI in learning activities (H7).

Perceived threats may be associated with the use of generative AI in learning activities. Al-Emran et al. (2025) found that perceived threats had a significant negative effect on students' use of generative AI. Similarly, Yin (2025) showed that perceived technological threats were associated with greater hesitancy to use generative AI. Together, these studies suggest that perceived threats can act as a barrier to technology use. However, Al Murshidi et al. (2024) found that awareness of ChatGPT's risks was positively associated with students' willingness to use it in the future. Although risk awareness differs from perceived threats, this finding suggests that recognizing the potential negative consequences of a technology can coexist with a willingness to use it. Although these findings concern different constructs and outcomes, they provide a limited empirical basis for considering a positive association. Accordingly, the positive relationship proposed in H8 is treated as a tentative, context-specific expectation rather than a direct prediction of TTAT. Based on these arguments, this study proposes that higher perceived threats are associated with increased use of generative AI in learning activities (H8).

According to Luckett (2023), Generative AI is artificial intelligence technology that could create content by itself. This technological advancement creates new challenges for regulators around the world. This technology use causes safety and ethical concerns, such as privacy violations and the potential to create false information. Therefore, there is a need for regulation, supervision, and transparency. Generative AI use may support social sustainability in education by providing tailored

explanations, simplifying complex content, and offering language assistance beyond classroom hours. Such support may reduce learning barriers and contribute to perceived inclusiveness, accessibility, and educational equity. However, these potential benefits depend on technological access, AI literacy, and institutional support; greater use alone does not guarantee equity. Based on these arguments, this study proposes that greater use of generative AI in learning activities is associated with higher levels of social sustainability in education (H9). Figure 1 presents the proposed research model and the hypothesized relationships among the constructs.

In Indonesia, accounting research has examined sustainability in relation to corporate financial outcomes. Julita et al. (2025) examined how the social and environmental dimensions of corporate sustainability performance relate to financial performance in listed manufacturing firms, while Sastroredjo et al. (2026) investigated the relationship between ESG controversy management and profitability under varying levels of financial opacity. In the context of accounting education, this study examines how students' use of generative AI is associated with their perceptions of social sustainability. It also examines how user satisfaction, privacy concerns, and perceived threats are associated with generative AI use.

Building on the arguments above, this study examines how service quality, system quality, and information quality relate to user satisfaction, and how satisfaction, privacy concerns, and perceived threats relate to generative AI use among accounting students in Indonesia. It also investigates the relationship between generative AI use and social sustainability in education. By bringing these relationships together within a single framework, the study contributes to understanding both the perceived benefits and risks of generative AI in accounting education. Its findings may inform institutional policies and guidance that support responsible use of generative AI and socially sustainable learning practices. Additionally, the study offers some contributions. First, it brings together selected constructs from the DeLone and McLean Information Systems Success Model and Technology Threat Avoidance Theory to examine how quality evaluations and threat perceptions relate to generative AI use within a single framework. Second, it extends the focus beyond satisfaction and technology use by examining their connection to social sustainability in accounting education. Third, it provides evidence from Indonesian accounting students that may inform teaching practices and institutional guidance on evaluating AI-generated information, protecting sensitive data, and supporting responsible use of generative AI in learning. Accounting students represent a theoretically relevant population because their learning activities require information accuracy, critical thinking, ethical judgment, and professional responsibility. Therefore, examining generative AI use among accounting students is particularly important for understanding how technological benefits and perceived risks relate to learning experiences and perceived social sustainability in accounting education.

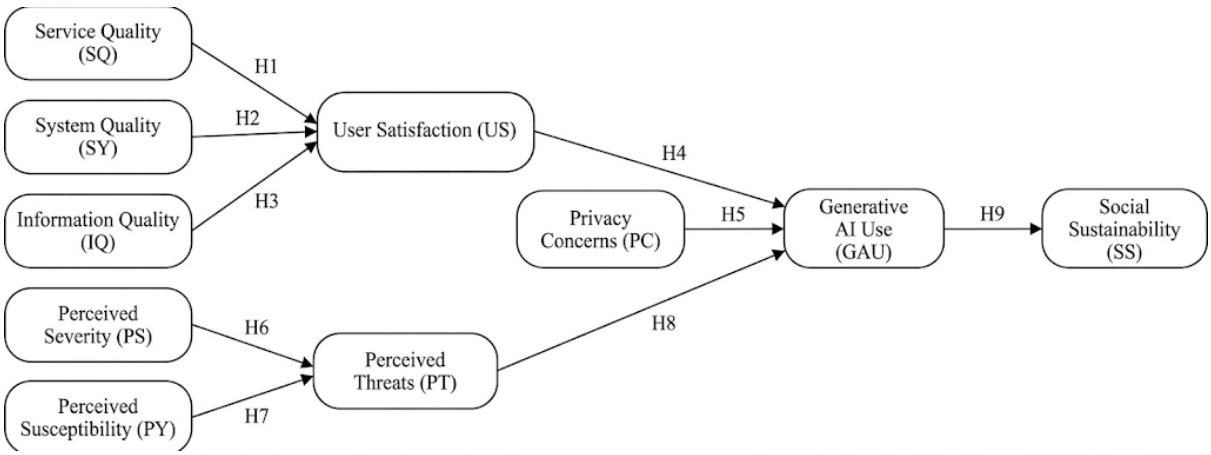

Figure 1. Research model

METHOD

This research uses a quantitative approach with a cross-sectional survey design. This approach is chosen because the data sample is large and spread geographically. Besides that, this approach is used to collect data easily and in a short amount of time, suitable for research on individual behaviour that is related to technology (Lim, 2024). As main method in collecting data in this research, online survey is used for validating research model that proposed and test hypothesis relation between variable. Survey method is used because it is considered more effective in predicting real behaviour and confirming relation between construct. Lecturer from various university or collage was asked to help out spread this questioner to their students that fill with question whether student already use to Generative AI in learning. The questionnaire was also spread through WhatsApp that consists of lecturer and student. All constructs were measured using multiple indicators adapted from previous studies, as presented in Table 1. Responses were recorded using a five-point Likert scale, ranging from strongly disagree to strongly agree.

Data were collected through an online survey over six months, from March to August 2026. Participation was voluntary, and respondents were informed that their responses would be treated anonymously and confidentially. These procedures were intended to encourage candid responses. Nevertheless, collecting all constructs from the same respondents through a single survey creates a potential risk of common method bias. Because the survey link was distributed through lecturer networks, the total number of eligible individuals who received the invitation could not be established. Therefore, a response rate could not be reliably calculated.

Population in this research is accounting student that has real experience in Generative AI use. Sampling method that uses is non-probability sampling, especially purposive sampling. The decision to use this method is based on time and cost efficiency, implementation convenience, and the ability to create relevant and quality data. Indonesia is chosen as the research location because of its social diversity, culture, and high digital literacy. These factors affect the way Generative AI is used in the educational environment. The study used a purposive sample of 150 accounting students in Indonesia with experience using generative AI in learning activities. Respondents were eligible to participate if they were accounting students enrolled in Indonesian higher education institutions and had prior experience using generative AI for learning activities. A screening question was included in the questionnaire to identify respondents' experience with generative AI.

Sample size considerations were evaluated retrospectively rather than through an a priori power analysis. Following Lakens (2022), the interpretation of the findings takes into account the information provided by the available sample and its limitations. The inverse square root method proposed by Kock & Hadaya (2018) indicates that 150 observations fall below the estimated requirements for the smaller structural paths in this study. Accordingly, the sample is not claimed to provide 80% power for all hypothesized relationships, and findings involving smaller coefficients are interpreted cautiously.

Data analysis begins with the assessment of measurement model validity and reliability using the average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (CA). Once the measurement model meets the established validity and reliability criteria, the structural model is evaluated using partial least squares structural equation modeling (PLS-SEM).

This method is used for checking connection of causality between laten construct and research hypothesis, and use for complex test model (Lowry & Gaskin, 2014). Some indicators are rated in structural model analysis for find out signification connection between variables. This includes path analysis, statistical rate, and p-value.

In PLS-SEM there are two kinds of model that create, is measurement model and structural model. The measurement model explains each manifest variable's proportion (indicator) that could be explained through a latent variable. In this research, there are 10 latent variables with a total of manifest variables as much as 36 indicators. Measurement model evaluation is done through construct reliability and average variance extracted. According to Hair et al. (2019), construct reliability is considered satisfactory if it is greater than 0,70 and average variance extracted (AVE) is expected to be greater than 0,50.

This study incorporates six exogenous variables: service quality, system quality, information quality, privacy concerns, perceived severity, and perceived susceptibility. The endogenous variables consist of user satisfaction, perceived threats, Generative AI usage, and social sustainability.

These variables are measured using indicators in Table 1:

Table 1. Variable Indicator

No	Variable Name	Indicator
1	Service Quality (Zhong & Chen, 2023)	1. Generative AI tool responds to my study needs quickly 2. Generative AI tool has knowledge to answer my question 3. Generative AI understands my specific study needs 4. Generative AI tool is always ready to help me
2	System Quality (Zhong & Chen, 2023)	1. The generative AI tool is easy to use 2. Generative AI tool can be used immediately 3. Generative AI tool helps me finish my study activity 4. Generative AI tool provides beneficial functions for my study activity
3	Information Quality (Zhong & Chen, 2023)	1. Information provided by the Generative AI tool is accurate 2. Information provided by Generative AI is always current 3. Information provided by Generative AI is easy to understand 4. Information provided by Generative AI is suitable for my study needs
4	User Satisfaction (Al-Sharafi et al., 2023)	1. My experience using the Generative AI tool is very satisfying 2. I felt happy to use Generative AI for learning 3. Overall, I am satisfied with the use of the Generative AI tool
5	Privacy Concerns (Jaspers, E. D. T. & Pearson, 2022)	1. I was worried my personal information collected by the Generative AI tool could be used for inappropriate purposes. 2. I worried my personal information collected by a generative AI tool could be accessed by an unknown party. 3. I felt the Generative AI tool was gathering too much of my personal information. 4. I was worried my personal information collected by Generative AI tool can be used with way that I don't know about.
6	Perceived Severity (Al-Sharafi et al., 2023)	1. I believed that a data privacy violation on a Generative AI platform may cause serious consequences. 2. The impact of receiving false information from Generative AI content might be very harmful. 3. If my personal information is accessed without permission through a Generative AI platform, the consequence might be very serious.
7	Perceived Susceptibility (Al-Sharafi et al., 2023)	1. I believed that I am at risk of experiencing private data problems while using a Generative AI platform. 2. I felt that my private information is vulnerable to unauthorized access through a Generative AI platform. 3. There is a big possibility that I will accept false or inaccurate information from a Generative AI platform. 4. I felt there is a possibility that Generative AI use can influence my critical thinking skills.
8	Perceived Threats (Baabdullah, 2024)	1. I am very worried about how far my private and sensitive information is shared and misused by Generative AI platforms. 2. The data misused possibility cause by interaction with Generative AI technology cause great anxiety for me. 3. I felt Generative AI use can caused risk in academic equity and integrity. 4. I worried Generative AI use can impact negatively on quality of long-term learning.
9	Generative AI Use (Al-Emran, 2023)	1. I often and routine use Generative AI tool. 2. I spend a lot of time using a Generative AI tool.
10	Social Sustainability (Al-Emran, 2023)	1. Generative AI adjusts learning activities to individual needs 2. Generative AI adjusts learning activities for various groups of users, so the learning experience becomes more inclusive 3. Generative AI adjusts learning activities based on local context and cultural nuances to increase learning understanding and relevance 4. Generative AI use impacts learning quality positively in the long term, so that it supports learning quality in a sustainable manner

RESULTS

Respondent characteristic of students is explained in detailed on Table 2. Based on gender, 62% of respondents are female, while 38% are male. On the age distribution side, the majority of participants, namely 67%, are in the age range of 18-20 years old, followed by 27% in the 21-22 years old, and 6% in the age range of 23-25 years old.

It can be seen 99,33% respondent studied using the help of Artificial Intelligence (AI) in their learning. Respondents have various levels of experience in using Generative AI tools. As much as 36% respondent has used AI technology everyday <1 hour, 43% respondent use AI technology for 1-2 hours per day, 16% respondent use AI technology for 2-3 hours per day, and 5% respondent has used AI help >3 hours every day. ChatGPT is the platform that mostly use, with 63,33% participant said that ChatGPT is main platform they use, followed by platform Gemini used as main platform by 25,33% participant. Meanwhile, other platforms like Copilot (0%) and another platform (11,33%) show a lower level of use.

Of the 150 respondents, 149 (99.33%) reported routinely using AI in learning activities, while one (0.67%) reported non-routine use. The latter respondent had prior experience using generative AI for learning and therefore met the study's eligibility criterion. The response concerned the regularity of use rather than the absence of previous experience. Respondents were accounting students from several universities in Indonesia, including UNPAR, UKM, UI, UNPAD, STIE Singkawang, and Universitas Nusantara Manado. Their years of entry ranged from 2022 to 2025. Table 2 summarizes their demographic characteristics and patterns of AI use in learning activities.

Table 2. Respondent Characteristics

No	Respondent Characteristics	Number	Percentage
1	**Gender**		
	Male	57	38
	Female	93	62
2	**Age**		
	18 – 20 years old	101	67
	21 – 22 years old	40	27
	23 – 25 years old	9	6
3	**AI is routinely used in learning activities**		
	Yes	149	99,33
	No	1	0,67
4	**AI platform most frequently used to support learning activities**		
	Chat GPT	95	63,33
	Gemini	38	25,33
	Copilot	0	0
	Others	17	11,33
5	**AI is used for a certain duration each day to support learning activities**		
	< 1 hour	54	36
	1 - 2 hours	64	43,00
	2 - 3 hours	24	16
	> 3 hours	8	6,00

Structural equation modelling (SEM) consists of two main components: the measurement model and the structural model. The measurement model assesses how well observed indicators represent their respective latent constructs, whereas the structural model examines the relationships among latent constructs. Hair et al. (2019) suggest that factor loadings of 0.70 or higher are generally desirable. Indicators with loadings below 0.50 are typically considered for removal from the measurement model. A measurement model is a model that connects latent variables with manifest variables. In this research there are 10 latent variables with number of manifest variables as much as 36 indicators. Measurement model evaluation is done through construct reliability and average variance extracted. According to Hair et al. (2019), construct reliability is considered satisfactory if it is greater than 0,70, and average variance extracted (AVE) is expected to be greater than 0,50.

Table 3. Measurement Model Test Results (Validity and Reliability)

Latent Variable	Cronbach's Alpha	CR	AVE
Service Quality (SQ)	0,807	0,874	0,634
System Quality (SY)	0,821	0,879	0,646
Information Quality (IQ)	0,811	0,875	0,637
User Satisfaction (US)	0,888	0,931	0,818
Privacy Concerns (PC)	0,919	0,887	0,667
Perceived Severity (PS)	0,792	0,878	0,707
Perceived Susceptibility (PS)	0,803	0,873	0,634
Perceived Threats (PT)	0,817	0,879	0,645
Generative AI Use (GAU)	0,767	0,896	0,811
Social Sustainability (SS)	0,888	0,922	0,748

Source: Processed data using SMART PLS 4, 2026

On table 3 can be seen construct reliability (CR) value each latent variable bigger than 0,70 show that indicator/manifest variable has consistency in measuring each latent variable. Then, an average variance extracted (AVE) value for each latent variable bigger than 0,50 show that, on average, more than 50% of the information contained in each indicator can be reflected through its latent variable. However, for the Privacy Concerns construct, Cronbach's alpha (0.919) was higher than composite reliability (rho_C = 0.887). Rechecking confirmed both values but also revealed a negative rho_A estimate (−0.442). Therefore, the reliability of this construct should be assessed with caution.

Table 4. Outer Loadings

Construct	Indicators	Outer loading
Service Quality (SQ)	SQ1	0.824
	SQ2	0.791
	SQ3	0.841
	SQ4	0.724
System Quality (SY)	SY1	0.762
	SY2	0.775
	SY3	0.853
	SY4	0.822
Information Quality (IQ)	IQ1	0.754
	IQ2	0.796
	IQ3	0.786
	IQ4	0.854
User Satisfaction (US)	US1	0.877
	US2	0.900
	US3	0.934
Privacy Concerns (PC)	PC1	0.690
	PC2	0.891
	PC3	0.707
	PC4	0.948
Perceived Severity (PS)	PS1	0.775
	PS2	0.877
	PS3	0.867
Perceived Susceptibility (PY)	PY1	0.861
	PY2	0.852
	PY3	0.782
	PY4	0.675
Perceived Threats (PT)	PT1	0.831
	PT2	0.830
	PT3	0.831
	PT4	0.715
Generative AI Use (GAU)	GAU1	0.906
	GAU2	0.895
Social Sustainability (SS)	SS1	0.892
	SS2	0.870
	SS3	0.870
	SS4	0.825

Source: Processed data using SMART PLS 4, 2026

Most indicator loadings in Table 4 exceeded 0.70. PC1 (0.690) and PY4 (0.675) were retained to preserve construct content coverage, considering the acceptable composite reliability and AVE values.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

Construct	GAU	IQ	PC	PS	PT	PY	SQ	SS	SY	US
GAU	—									
IQ	0.596	—								
PC	0.063	0.106	—							
PS	0.353	0.355	0.358	—						
PT	0.232	0.140	0.578	0.512	—					
PY	0.148	0.226	0.811	0.568	0.800	—				
SQ	0.627	0.682	0.073	0.477	0.133	0.266	—			
SS	0.651	0.699	0.168	0.514	0.305	0.382	0.680	—		
SY	0.703	0.620	0.087	0.533	0.161	0.290	0.921	0.711	—	
US	0.675	0.817	0.064	0.377	0.114	0.157	0.772	0.708	0.748	—

Source: Processed data using SMART PLS 4, 2026

Among the available HTMT values in Table 5, all were below 0.90 except the System Quality–Service Quality pair (0.921), indicating a discriminant validity concern. Accordingly, their separate relationships with user satisfaction should be interpreted cautiously.

Based on the processing results, the full path diagram model is as follows in Figure 2.

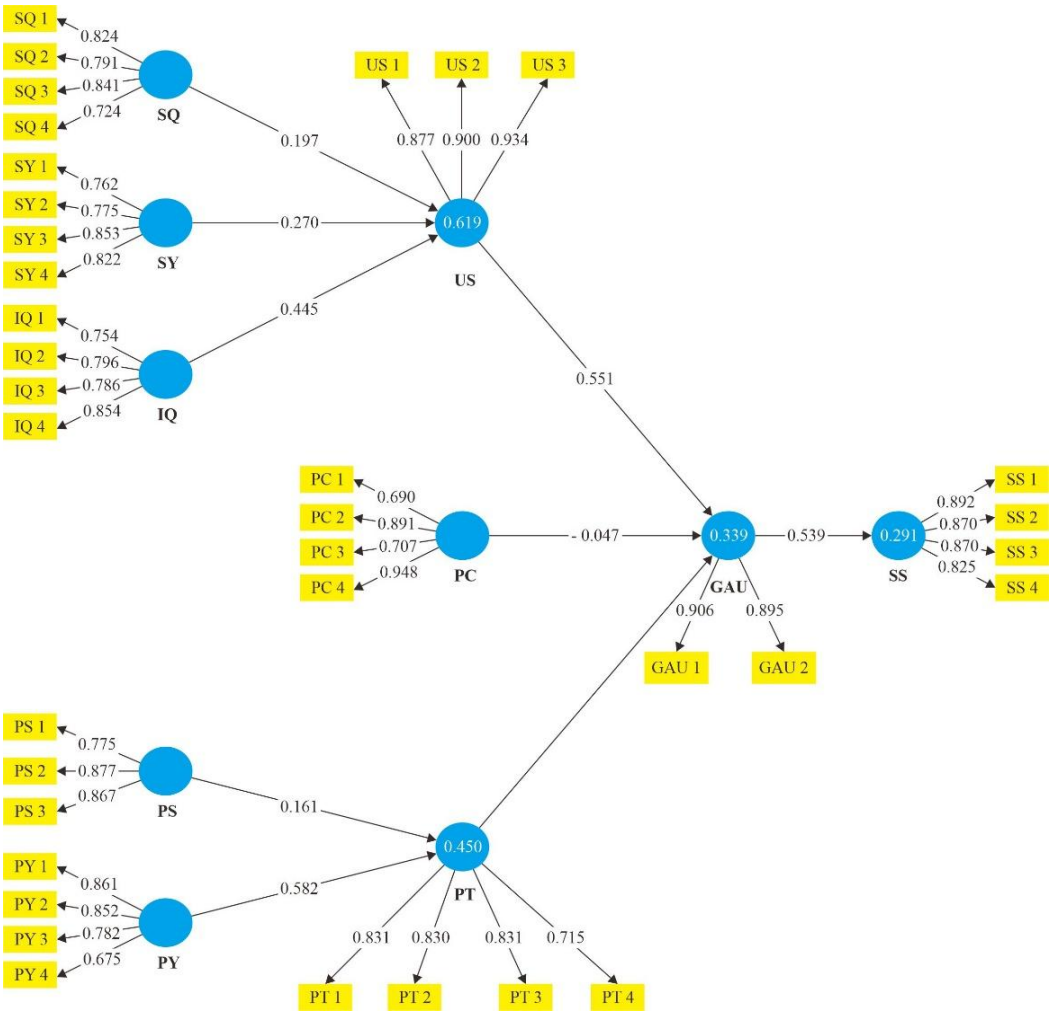

Figure 2. Full Model Path Diagram

The structural model is a model that connects latent variables with other latent variables for testing the effect of exogenous latent variables on endogenous latent variables. Here is summary of values used on testing structural model.

Table 6. Direct Effect Test Results

Direct Effect	Coefficient	$T_{statistics}$	P_{values}	R^2	Hypothesis
Service Quality (SQ) → User Satisfaction (US)	0,197	2,055	0,040	0,619	H1 - Supported
System Quality (SY) → User Satisfaction (US)	0,270	3,252	0,001	0,619	H2 - Supported
Information Quality (IQ) → User Satisfaction (US)	0,445	8,575	<0,001	0,619	H3 - Supported
Perceived Severity (PS) → Perceived Threats (PT)	0,161	2,183	0,029	0,45	H6 - Supported
Perceived Susceptibility (PY) → Perceived Threats (PT)	0,582	8,728	<0,001	0,45	H7 – Supported
Privacy Concerns (PC) → Generative AI Use (GAU)	-0,047	0,437	0,662	0,339	H5 - Not Supported
User Satisfaction (US) → Generative AI Use (GAU)	0,551	8,285	<0,001	0,339	H4 - Supported
Perceived Threats (PT) → Generative AI Use (GAU)	0,182	2,114	0,035	0,339	H8 - Supported
Generative AI Use (GAU) → Social Sustainability (SS)	0,539	7,746	<0,001	0,291	H9 - Supported

Influence of Service Quality (SQ) on User Satisfaction (US). On table 6 can be seen coefficient path has positive value and t-statistic as big as 2,055 > 1,96 and value of p-value 0,040 < 0,05, then on level of error 5% can be concluded first hypothesis (H1) is accepted where Service Quality affects positively and significantly to User Satisfaction.

Influence of System Quality (SY) on User Satisfaction (US). As presented in Table 6, the path coefficient is positive, with a t-statistic of 3.252, exceeding the critical value of 1.96. The p-value is 0.001, which is below the 0.05 significance threshold. Therefore, at the 5% significance level, the second hypothesis (H2) is supported, indicating that system quality has a positive and statistically significant effect on user satisfaction.

Influence of Information Quality (IQ) on User Satisfaction (US). The results reported in Table 6 indicate a positive path coefficient for the relationship between information quality and user satisfaction. The t-statistic of 8.575 exceeds the critical value of 1.96, while the p-value is below the 0.05 significance level. These findings provide statistical support for the third hypothesis (H3), demonstrating that information quality has a positive and statistically significant effect on user satisfaction at the 5% significance level.

Influence of Perceived Severity (PS) on Perceived Threats (PT). The findings presented in Table 6 show that perceived severity has a positive path coefficient in its relationship with perceived threats. The t-statistic of 2.183 exceeds the critical value of 1.96, while the p-value of 0.029 is lower than the significance threshold of 0.05. Accordingly, the sixth hypothesis (H6) is supported at the 5% significance level, indicating that perceived severity has a positive and statistically significant effect on perceived threats.

Influence of Perceived Susceptibility (PY) on Perceived Threats (PT). The results in Table 6 demonstrate a positive relationship between perceived susceptibility and perceived threats. The t-statistic reaches 8.728, exceeding the critical value of 1.96, while the p-value is below 0.05. These results provide empirical support for the seventh hypothesis (H7) at the 5% significance level, suggesting that perceived susceptibility has a positive and statistically significant effect on perceived threats.

Influence of Privacy Concerns (PC) on Generative AI Use (GAU). In Table 6, the coefficient path has a negative value and a t-statistic of 0,437 < 1,96 and a p-value of 0,662 > 0,05; therefore, at the 5% significance level, the fifth hypothesis (H5) is rejected. Privacy concerns do not affect Generative AI Use.

Influence of User Satisfaction (US) on Generative AI Use (GAU). On table 6 can be seen coefficient path has positive value and t-statistic as big as 8,285 > 1,96 and value of p-value <0,001, then on level of error 5% can be concluded fourth hypothesis (H4) is accepted where User Satisfaction affects positively and significantly to Generative AI Use.

Influence of Perceived Threats (PT) on Generative AI Use (GAU). On table 6 can be seen coefficient path has positive value and t-statistic as big as 2,114 > 1,96 and value of p-value 0,035 < 0,05, then on level of error 5% can be concluded eighth hypothesis (H8) that Perceived Threats affects positively and significantly to Generative AI Use.

Influence of Generative AI Use (GAU) on Social Sustainability (SS). As shown in Table 6, the path coefficient for the relationship between Generative AI use and social sustainability is positive. The t-statistic of 7.746 exceeds the critical value of 1.96, while the p-value is below the 0.05 significance threshold. Therefore, the ninth hypothesis (H9) is supported at the 5% significance level, indicating that Generative AI use has a positive and statistically significant effect on social sustainability.

Besides, in Table 6, the R2 (R-square) shows that the model's ability to explain the dependent variable is decent. User Satisfaction has R^2 0,619 that means 61,9% US has successfully explained by indicator SQ, SY, and IQ. After that, Perceived Threats has R^2 0,450 that mean 45% of PT is successfully explained by the PS and PY indicators. Then, Generative AI Use has R^2 0,339 where 33,9% GAU can be explained by PC, US, and PT indicators. Lastly, Social Sustainability has R^2 0,291 that show 29,1% has been explained by GAU.

DISCUSSION

This research has purpose for exploring how quality aspect, privacy concerns, and severity level perception and threats can influence use of artificial intelligent (AI) technology and push the formation of social sustainability in education world. This model test in empirical way using data collected from accounting student in Indonesia and data is processed using PLS-SEM method for testing submitted hypothesis.

PLS-SEM results in this research show that Service Quality (SQ) has a positive and significant effect on User Satisfaction (US). This finding parallel with previous research shows that service quality is important for increasing user satisfaction. This finding says that students will be more satisfied when using Generative AI tools that are reliable, easy to use, and supported by responsive support service. Because of that, the better the service that students receive, the more satisfied they are with Generative AI use in learning help and solving assignments that are available (AbdelKader & Sayed, 2022). But on certain context, service quality is not significant to temporal satisfaction of information quality and system that affect significant, its imply that service quality is not enough (Berényi et al., 2025; Wu & Fan, 2024). In accounting education, this finding suggests that responsive support may contribute to students' satisfaction by helping them obtain timely assistance when working through accounting exercises and assignments(Blondeel et al., 2025).

The results of this research also show that System Quality (SY) has a positive and significant effect on User Satisfaction (US). This finding parallel with previous research that emphasize importance of content accuracy created by AI, speed in responding question, ease of use the system, and consistency in providing relevant information is very important in increasing user satisfaction (Hidayat et al., 2024; Wei et al., 2022). Quality of AI system is really affecting to satisfaction or intention of user, but not the only determine factor. Other factors such as quality of information, service, trust, experience, and perception of use are also important (Ngo et al., 2025). For accounting students, this relationship may reflect the value of convenient and accessible learning support when seeking help with accounting tasks (Blondeel et al., 2025).

Besides that, the results of research also show Information Quality (IQ) has positive and significant to User Satisfaction (US). This finding parallel with previous research that found artificial intelligent technology create relevant, useful, easily understand, accurate, reliable, latest, and available information on needed time will increase user satisfaction(Wang et al., 2024). But there is research that found information quality precisely has negative effect on satisfaction and not significant to sustainable user, precisely that push user is quality of system and service also user trust(Abdellatief & Alotaibi, 2026). This finding is particularly relevant to accounting education because the accuracy of AI-generated explanations and solutions varies across accounting tasks, making reliable information and verification important for learning (Cheng et al., 2024). These findings are consistent with the Information Systems Success Model, which emphasizes the importance of service quality, system quality, and information quality in shaping user satisfaction. In accounting education, these relationships suggest that students' satisfaction with generative AI may depend not only on its accessibility and responsiveness but also on the perceived reliability and relevance of information used to support accounting-related learning activities.

User Satisfaction (US) affects positively and significantly to Generative AI Use (GAU). In this research, respondent felt satisfy with generative AI use can help them in learning process and make this technology use increase. This is parallel with previous research that said user satisfaction makes AI technology use increase (Park & Lee, 2024). In accounting education, this association suggests that satisfactory experiences with AI-assisted learning may encourage further use, although greater use should not be equated with better learning outcomes (Blondeel et al., 2025).

The results of this research show that Privacy Concern (PC) does not affect Generative AI Use (GAU), meaning that higher privacy concerns do not affect the use of AI technology itself, but this finding should be interpreted with caution due to the anomalous reliability estimate for the Privacy Concerns construct. This is not parallel with previous research that said PC has a negative and significant connection to GAU (Yao, Q. et al., 2024), where privacy concerns are the main obstacle factor in adopting AI technology. One possible explanation is that students may prioritize the perceived academic benefits of generative AI despite concerns about personal data protection. Alternatively, students may believe that they can reduce privacy risks by limiting the personal information shared with AI tools. However, these explanations were not directly examined in this study. Furthermore, the anomalous reliability estimate for the Privacy Concerns construct requires caution when interpreting its non-significant relationship with generative AI use.

Perceived Severity (PS) affects Perceived Threats (PT). The results of this research show that privacy violations can cause serious consequences; the impact of receiving false information from AI can be harmful, and personal information spread without permission can also cause serious consequences. This is parallel with previous research that found PS level can include anxiety about privacy violations of personal data, misuse of content created by technology, or ethical problems that appear from technology. This finding shows that the more students see negative effects of GAU, the more their perception of threats related to technology use increases (Shiva et al., 2023).

Previous research said that the level of severity or risk caused by Generative AI precisely increases user awareness. While users obtain information from Generative AI, they will first check the truth of that information or even avoid inserting personal data. So, empirically, PS indeed influences PT, which later increases individual awareness (Lee et al., 2025).

The research result also shows Perceived Susceptibility (PY) affects positively and significantly to Perceived Threats (PT). from questioner result, show that respondent realize there is risk in AI use, including: privacy problem, risk to unauthorized access, get false or inaccurate information, and risk in influencing critical thinking skill. Perceived susceptibility measures the chances of risk. This research parallel with previous research that indicate the higher level of vulnerability respondent felt, the bigger threats regulation they felt (Ivanov et al., 2024; Yin, 2025). For accounting students, this relationship reinforces the need to recognise their own vulnerability to misleading AI outputs and to practise checking accounting solutions rather than accepting them without evaluation (Cheng et al., 2024).

Furthermore, the results show that Perceived Threat (PT) is positively and significantly associated with Generative AI Use (GAU). This means that respondents who perceive greater threats

tend to report higher levels of generative AI use. These threats include concerns about the misuse of personal data, risks to academic equity and integrity, and potential negative effects on long-term learning quality. This finding differs from Al-Emran et al. (2025), who found a significant negative effect of perceived threats on generative AI use, and Yin (2025), who showed that perceived technological threats were associated with greater hesitancy to use generative AI. However, it broadly aligns with (Al Murshidi et al. 2024), who found a positive relationship between awareness of ChatGPT's risks and students' willingness to use it in the future. Although the constructs and measures of use differ, their study suggests that awareness of risks can coexist with a willingness to use the technology. One possible explanation is that students continue to use generative AI because they consider its academic benefits to outweigh the perceived risks. Another possibility is that students who use generative AI more frequently become more aware of its potential threats. However, neither explanation was directly tested in this study. Therefore, the positive relationship should be interpreted as an association between the variables rather than evidence that greater perceived threats cause increased generative AI use. For accounting education, the coexistence of perceived threats and greater AI use points to the importance of guided integration that preserves students' independent reasoning and academic integrity rather than assuming that awareness of risks alone will discourage use (Ballantine et al., 2024).

The findings provide a context-specific assessment of the quality–satisfaction–use relationships proposed by the Information Systems Success Model. For the selected TTAT constructs, the positive association between perceived threats and generative AI use challenges a straightforward interpretation of threats as barriers to use. However, this finding does not invalidate TTAT, as the study does not examine its full coping-appraisal and avoidance mechanisms.

Parallel with previous research (Al-Emran et al., 2025; Foroughi et al., 2025; Xiao et al., 2025) that said Generative AI Use (GAU) affects Social Sustainability (SS) positively and significantly, this research also found a similar thing: increasing use of AI technology will create social sustainability. In accounting education, this association provides a basis for further investigating whether structured AI support can meet diverse learning needs, particularly those of lower-performing students, while recognising that improved educational equity was not established by the present study (Blondeel et al., 2025).

Generative AI use was positively and significantly associated with perceived social sustainability among the accounting students surveyed. However, these self-reported perceptions do not demonstrate that generative AI use contributes to the achievement of SDG 4 or reduces educational inequality. Social sustainability in education includes fairness, equity, and accessibility for diverse groups of students. Generative AI may offer opportunities to adapt learning materials to students' needs and support learning across different languages, although these potential benefits were not directly assessed in this study. Previous research has also raised concerns that AI use without appropriate governance may undermine social sustainability (Patrício et al., 2024; Rawashdeh, 2025).

CONCLUSION

Base of analysis data result and discussion that have been done, this research results some conclusion such as Service Quality, System Quality, Information Quality were positively and significantly associated with User Satisfaction. This shows that students will be satisfied if a Generative AI tool is reliable, easy to use, gives fast responses, and provides accurate and relevant information for academic needs.

The interesting finding in this research is that Privacy Concerns were not significantly associated with Generative AI Use. Student tend to stay using AI despite aware of data risk, possibly because needs of efficiency in long learning is greater than feel of worry, or because lack of deep understanding about private data issue. Despite privacy concerns in general does not stop user, perception to Perceived Severity and Perceived Susceptibility is proven to increase Perceived Threats. This Perceived Threats in significant affect duration and behaviour of this technology user.

Besides that, Generative AI use affects Social Sustainability positively and significantly in an academic environment. This technology help to create learning that more inclusive, adaptive, and can be accessed widely, that parallel with the achievement of SD 4 (quality education). Theoretically, this study contributes to the Information Systems Success Model by providing empirical evidence of the relationships among service quality, system quality, information quality, user satisfaction, and generative AI use in accounting education. Furthermore, the findings related to perceived severity, perceived susceptibility, and perceived threats are consistent with the threat appraisal mechanisms described in Technology Threat Avoidance Theory (TTAT). Interestingly, the positive association between perceived threats and generative AI use suggests that threat perceptions may coexist with continued technology use, highlighting a relationship that warrants further theoretical investigation. By integrating these perspectives, this study also extends the discussion of generative AI adoption to its association with perceived social sustainability in accounting education.

Base of research result, some recommendation can be given to various stakeholders. For collage institution, is needs for arrange policy and governance of proper Generative AI use as ethic guidelines for students in utilize this technology on academic activity. This policy can hopefully keep academic integrity while also preventing over-dependency so that students' critical and analytical thinking skills keep improving. Besides that, university need to increase digital literation and artificial intelligent literation through training or education program that emphasize the importance of data security, and responsible AI use. This is become important because the research results show that student tend to more prioritize functional benefits of Generative AI than privacy risk potential.

For Generative AI technology developers, the research results show that service quality, system quality, and information quality are the main factors that influence user satisfaction. Because of that, developers must continue to increase accuracy, relevance, and up-to-date information created, include with enhancement of system security aspect for increasing user trust. Besides that, more inclusive feature development, such as support for local language, cultural context, and the needs of diverse users, can further strengthen Generative AI's contribution in creating an academic environment that is fair, inclusive, and sustainable.

This study has several limitations. The relatively small sample of 150 accounting students, selected through non-probability sampling, limits the generalisability of the findings to other student populations. All constructs were measured using self-reported data from a single source, making them potentially susceptible to response bias and common method bias. The cross-sectional design also prevents causal conclusions and does not capture changes in perceptions and use over time. In addition, the anomalous reliability estimates for the Privacy Concerns construct warrant caution when interpreting findings involving this variable. In addition, the respondents are limited to accounting students, so the findings may not apply to students from other disciplines. Furthermore, all constructs were measured using a single self-reported questionnaire, which may introduce common method bias. No dedicated statistical assessment of common method bias was conducted; therefore, its potential influence on the estimated relationships cannot be ruled out, and the findings should be interpreted with caution.

For future research, this study still has room for development. Future research is recommended to expand the scope of respondent with involving student from various disciplines, and insert lecturer perspective as well as educational institute administrator so that obtained more comprehensive image about Generative AI use in university environment. Besides that, because this research uses a cross-sectional design, longitudinal study is very recommended to examine behavioural change in Generative AI use and its impact to learning quality, critical thinking skill, and social sustainability in long term.

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AI Disclosure

The authors used ChatGPT to brainstorm ideas, explore possible interpretations of the findings, and refine the wording of the manuscript. All data analyses and statistical calculations were performed and verified by the authors. The authors generated the empirical results, independently evaluated their interpretation, and drew the study's conclusions. The authors take full responsibility for the content and conclusions of this study.