Large Language Models in Accounting Tasks: Driving Factors and Ethical Dilemmas Among Accounting Students

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***Abstract*— This research aims to identify the key factors that affect accounting students' intention to adopt and the actual usage of Large Langauge Models (LLMs), including ChatGPT, in academic contexts. It also addresses ethical concerns that may arise from their use. Using a quantitative design, data were collected through an online survey involving 302 students from various universities in the Greater Jakarta area who had prior experience using LLMs. This research aims to address the gap in literature on AI-based technology acceptance within the accounting field by extending the Technology Acceptance Model (TAM) with trust and academic ethics. The study offers a theoretical contribution by deepening insights into technology acceptance within accounting education and a practical contribution by emphasizing the integration of ethical considerations in the use of LLMs in higher education. The study focuses on key constructs including perceived ease of use, perceived usefulness, trust, academic ethics, behavioral intention, and actual usage behavior. Data was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique via SmartPLS 4 software. The results show that all examined factors positively influence students' intention to use LLMs, with perceived usefulness stands out as the most significant driver. Furthermore, behavioral intention significantly predicts actual use, suggesting that students who see practical value in these tools are more likely to adopt them in their learning routines. What sets this research apart is its integration of motivational and ethical dimensions in examining technology acceptance within accounting education.**

Keywords*— *Large Language Models, Technology Acceptance, Academic Ethics, Behavioral Intention, Accounting Education

I. INTRODUCTION

The adoption of artificial intelligence (AI) has grown swiftly in recent years, especially with the rise of ChatGPT as one of the most popular generative AI models. Technologies like Large Language Models (LLMs) have drawn global interest due to their ability to generate contextually appropriate text, making them useful across a range of sectors from education to business and the creative industries. In Indonesia, public awareness of LLMs has also increased significantly. The BCG Global Consumer Sentiment Survey 2024 [1] reports that public awareness of LLM technology in Indonesia has reached 83%, with 32% of respondents actively using it. Among the Southeast Asian countries included in the survey, Indonesia has a higher usage rate than the Philippines (28%) and Thailand (14%) [1]. This suggests that LLMs are becoming more integrated into everyday activities in Indonesia, including academic work, offering both opportunities and challenges.

For students, LLMs can support learning by simplifying complex material and assisting with academic writing tasks such as summarizing, paraphrasing, and outlining texts [2], [3]. Specifically, the features of LLM technology can help accounting students with financial data processing, assistance in preparing financial statements, as well as audit and compliance. LLM technology can simplify transaction recording, categorize accounting data, and provide financial report summaries that are easier to understand [4]. In addition, this tool can be used to analyze financial trends like providing brief summaries of finansial reports, which is useful for budgeting tasks and financial management [5].

However, alongside its benefits, the use of LLM technology also presents ethical dilemmas including concerns of plagiarism and academic dishonesty, a decline in critical thinking skills, as well as potential copyright and privacy violations due to biased or inaccurate output [6]. Furthermore, Ref. [6] expressed concerns that excessive reliance on LLM technology may lead to a decrease in analytical abilities and increased laziness [7]. In this context, understanding how students navigate the trade-off between technological advantages and emerging ethical challenges becomes essential.

This study employs the Technology Acceptance Model (TAM) framework to understand the determinants influencing the adoption of Large Language Models (LLMs) technology. TAM is a theoretical framework positing perceived ease of use and perceived usefulness are the main predictors of an individual's behavioral intention to use technology [8]. In this study, TAM is modified by adding the variables of trust and academic ethics (academic integrity) [9]. Academic ethics, also referred to as academic integrity [9], represents a dedication to core values including honesty, trust, fairness, respect, responsibility, and courage throughout the learning process and

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the production of scholarly work [10].

Perceived ease of use (PEOU) has become one of the core constructs in the Technology Acceptance Model. Previous research shows that the perception of ease of use has a positive influence on users' intention to adopt new technologies, including artificial intelligence (AI) in academic context [11]. However, a study by Ref. [12] involving 330 accounting and auditing students at a private university in Lebanon found contradictory results: PEOU did not significantly affect AI adoption, while perceived usefulness (PU) and technology readiness (TR) were the dominant factors.

Perceived usefulness (PU) refers to the degree to which a person believes that using a particular technology can enhance productivity and performance [11]. Previous studies have highlight a strong link between perceived usefulness and users' willingness to adopt technology, especially if the technology is considered relevant to their tasks or work [11], [12]. However, research by Ref. [13] found that this relationship was not significant among accounting students in Batam when examining AI adoption.

Furthermore, trust serves as a crucial element in technology adoption, as users tend to be more accepting of systems they consider trustworthy [14]. Prior research has indicated that the degree of users' trust in AI and technology-based systems greatly determines the success of technology implementation [15]. Research by Ref. [16] emphasizes that risk-benefit perceptions also influence users' trust in LLM technology, indicating that even when trust is high, users remain cautious about the possible risks and rewards of these technological tools. This demonstrates that the decision to adopt such technologies is based on various considerations, not trust alone.

The ethical dimension in the use of technology is becoming an increasingly primary concern, especially with the rise of generative AI such as LLM technology. Deloitte's annual 'Ethical technology standards' survey finds that 54 % of respondents consider AI the most ethically risky emerging technology, and that failure to uphold ethical principles is seen as a significant reputational threat to long-term success [17]. However, there is an interesting contradiction between ethical risk awareness and usage behavior. Many students continue to adopt LLM technology for various academic tasks without giving in-depth consideration to ethical aspects [18], [19]. The findings from [18], [19] raises the question of whether ethical perception truly plays a role in technology usage decisions, or if it merely amounts to passive awareness.

These findings [1], [2], [3], [4], [5], [6], [7], [8], [9], [11], [12], [13], [14], [15], [16], [17], [18], [19] indicate the presence of a gap that affects AI usage behavior within the TAM framework, namely perceived ease of use (PEOU), perceived usefulness (PU), trust, and academic ethics. This gap highlights the importance of reevaluating the contextual relevance of these variables, especially from the perspective of accounting students in their use of LLM technology, to understand other factors that may have a greater influence on their decision to utilize AI technology.

While numerous studies have applied the Technology Acceptance Model (TAM) to examine technology adoption across various sectors, few have specifically combined aspects of trust and ethical awareness in the context of how accounting students engage with LLM technology. Furthermore, few research efforts have concurrently explored the ethical dilemmas of using AI in academic assignments alongside technology acceptance factors. Therefore, this research aims to fill this gap by examining the driving factors behind accounting students' behavioral intentions to use LLM technology while considering its ethical dilemmas.

The rapid rise of LLMs like ChatGPT in academic settings has created an urgent need to understand how accounting students navigate their use responsibly. As these tools become increasingly integrated into learning and assessment processes, understanding the balance between technological acceptance and ethical awareness becomes essential to prevent academic misconduct and preserve professional integrity in future accountants.

This study addresses the following questions by adopting and modifying the TAM model while also considering aspects of trust and academic integrity:

1. Does perceived ease of use influence the behavioral intention of accounting students in using LLM technology?
2. Does perceived usefulness influence the behavioral intention of accounting students in using LLM technology?
3. Does trust influence the behavioral intention of accounting students in using LLM technology?
4. Does academic ethics influence the behavioral intention of accounting students in using LLM technology?
5. Does behavioral intention influence the use behavior of LLM technology among accounting students?

By answering these questions, this study aims to offer valuable understanding for developing effective approaches to integrate LLM technology into accounting education while also promoting responsible and ethical use.

A. Acceptance Model for LLM Technology Adoption

The technology acceptance model is a continuously developing area of research [20], especially in examining the adoption of emerging technologies such as Large Language Models (LLMs), including ChatGPT, Perplexity, and Gemini. In academic settings, technology acceptance models help identify the factors that affect students' use of technology for learning purposes.

Among the theoretical frameworks addressing user acceptance of technology, the Technology Acceptance Model (TAM), developed by Ref. [21], is regarded as one of the most established and widely utilized. TAM emphasizes two main variables: perceived usefulness (PU) and perceived ease of use (PEOU), which are essential in determining users' intentions to adopt technology. Recent studies highlight that understanding how students accept LLM technology offers valuable insights

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for enhancing the effectiveness of educational tools. Research conducted by Ref. [22] indicates that within medical training in the United Arab Emirates, perceptions of usefulness (perceived usefulness) and ease of use (perceived ease of use) significantly affect students' tendency to utilize AI in learning. These findings illustrate that in technology-based educational contexts, including LLMs, perceptions of usefulness and ease of use can be important factors influencing students' intention to use technology.

Another key determinant of LLM technology acceptance is trust. Users must feel confident that the technology is reliable, accurate, and safe to use [23]. Previous research has shown that trust can influence the connection between perceived usefulness and behavioral intention in digital technology adoption [24]. In the context of LLM, aspects of trust include transparency in data processing, information security, and the system's capability to provide relevant and ethical output [23].

Academic ethics or academic integrity [9] is also a crucial factor influencing the acceptance of LLM technology, especially in academic contexts where issues such as plagiarism and information reliability are major concerns [25].

By considering these various factors, the acceptance model for LLM technology adoption can be designed by integrating elements from TAM and additional factors such as trust and academic ethics. Thus, this study offers deeper understanding of the factors that drive or hinder the use of LLM technology, particularly among accounting students in their academic and professional contexts. The research model in this study is illustrated in Figure 1.

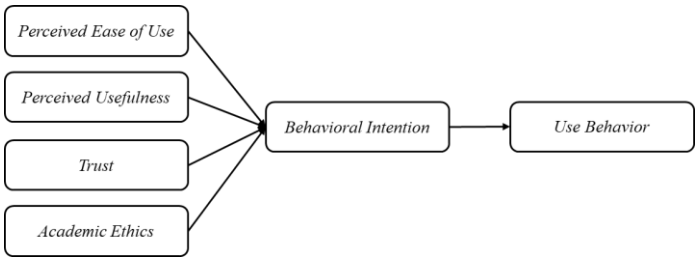

Fig. 1. Research model.

B. Perceived Ease of Use (PEOU) – Behavioral Intention

Perceived ease of use (PEOU) is defined as users' perception that a technology can be utilized effortlessly and understood with minimal difficulty [21]. Within the LLM technology context, ease of use becomes a crucial factor for accounting students who are often faced with complex tasks. Research by Refs. [22], [26], [27] shows that PEOU has a significant effect on students' adoption behavior toward information technology. Study by Ref. [22] on the metaverse technology adoption also found similar results, that PEOU influences intention to use. These findings reinforce the TAM framework by showing that perceived ease of use has a direct and positive impact on students' behavioral intention to adopt technology in educational contexts. In other words, ease of use influences students' readiness (both mentally and technically) to face new technologies, such as LLM. Hence, the more user-friendly the LLM technology, the greater students' intention to adopt it in their academic work. The first hypothesis is as follows:

H1: Perceived ease of use influences the behavioral intention of accounting students in using LLM technology

C. Perceived Usefulness (PU) – Behavioral Intention

Perceived usefulness (PU) represents users' belief that the use of a technology will enhance their performance [28]. LLM technology is considered useful for accounting students because it can accelerate financial data analysis and provide conceptual explanations [29].

[30] showed that perceived usefulness serves as a primary determinant of behavioral intention, especially when technology has been proven to optimize learning outcomes. Reference [30] findings correspond with the study conducted by Ref. [31], which identified that PU significantly influences users' behavioral intentions in utilizing digital applications, even outside the educational context. Reference [32] also found that PU influences students' acceptance of AI-based tools such as LLM technology. When students perceive that LLM technology enhances their learning, they are more likely to accept and use it. Thus, the more value they find in the technology, the stronger their intention to apply it regularly in academic work. The second hypothesis is:

H2: Perceived usefulness affects accounting students' behavioral intention to use LLM technology.

D. Trust – Behavioral Intention

Trust represents the degree to which users have confidence that a technology will operate reliably and uphold its intended purpose [33]. Reference [30] demonstrated that trust plays an important role in shaping attitudes toward LLM technology. According to Ref. [30], first-year students feel comfortable and motivated to use LLM technology when they are confident that it is safe and dependable.

Similar findings were reported by Ref. [34], which identified that trust as one of the three strongest determinants of future intention to engage with LLM technology, alongside perceived usefulness. Reference [33]'s study of business professionals also emphasizes that trust is one of the main predictors of the intention to adopt LLM technology. Overall, it can be concluded that the greater the trust students place in LLM technology, the stronger their intention to engage with it in academic contexts. The third hypothesis is as follows:

H3: Trust influences the behavioral intention of accounting students in using LLM technology.

E. Academic Ethics – Behavioral Intention

Academic ethics, or academic integrity [9] embodies the commitment to upholding fundamental values such as honesty, trust, fairness, respect, responsibility, and courage in the process of learning and producing scholarly work [10]. These values require every individual to be honest in academic work,

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maintain the originality of their work, respect others' work, and be responsible for all academic activities, thereby creating a fair and trustworthy learning and research environment.

[35] showed that students who understand the ethical risks of using LLM technology, such as excessive dependence or copyright infringement, tend to have a lower intention of irresponsible usage. This finding aligns with the findings of Ref. [36], who integrated ethical considerations into the UTAUT model and found that ethical awareness strongly influences the intention to adopt educational technology. However, research by Ref. [37] notes that attitudes (positive perceptions toward LLM technology) often override ethical considerations if students feel that the technology can increase task efficiency. This combination of factors indicates that academic ethics not only serve as an inhibitor but can also be a driver of behavioral intention. The fourth hypothesis is:

H4: Academic integrity (academic ethics) has a positive and significant influence on accounting students' behavioral intention to use LLM technology.

F. Behavioral Intention to use LLM

Behavioral intention is the main predictor of use behavior (actual behavior) in technology adoption, as described in the Unified Theory of Acceptance and Use of Technology (UTAUT) [38]. A study by Ref. [30] involving accounting students showed that behavioral intention towards LLM technology significantly influences use behavior, especially when the technology is seen as useful and easy to operate. Reference [30] found that behavioral intention strongly predicts use behavior, with students who have high intention being more likely to use LLM technology for financial analysis tasks and report preparation.

H5: Behavioral intention has a positive and significant effect on the use behavior of LLM technology among accounting students.

II. RESEARCH METHODS

This study is employs a quantitative research approach, with data collected through surveys via digital questionnaires (Google Form). The questionnaires are distributed by utilizing digital questionnaires (Google Forms) distributed through WhatsApp and Instagram to reach accounting students from various universities in the Greater Jakarta area (Jabodetabek). The selection of accounting students in the Greater Jakarta area is based on the region's position as Indonesia's largest higher education and economic center, where many universities actively integrate technology into accounting education. Students in this area generally have higher exposure to digital innovations and AI tools such as ChatGPT due to better internet access and institutional support. Therefore, they represent a relevant and contextually appropriate sample for examining behavioral and ethical aspects of LLM usage in accounting education.

The study targets active accounting students who had used ChatGPT or similar LLM technology for academic purposes. Purposive sampling is used, with a total of 302 respondents successfully collected.

This study adapted measurement indicators from prior studies, modified to fit the current research context. The study utilized a 5-point Likert scale to measure respondents' agreement with each statement, where 1 represented "Strongly Disagree" and 5 represented "Strongly Agree."

The conceptual framework of this study comprises six primary constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trust (T), Academic Ethics (AE), Behavioral Intention (BI), and Use Behavior (UB). The statements for each construct in this questionnaire are adapted and modified from several relevant studies. The indicators for the variables Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Behavioral Intention are adapted from Refs. [26], [30]. The indicators for the Trust variable are adopted from Refs. [16], [30], [32]. The Academic Ethics variable refers to indicators developed by Refs. [39], [40]. The indicators for the Use Behavior variable are adapted from Refs. [8], [16], [40].

The data obtained are analyzed using SmartPLS 4 software. The Partial Least Squares-Structural Equation Modeling (PLS-SEM) method is applied, as it is suitable for research models that examine relationships between latent variables with multiple indicators. Based on Refs. [41], [42], [43], [44], the analysis was conducted in two primary stages:

1) *Outer Model Measurement:*
   - Convergent Validity, with the criteria of a loading factor value > 0.7 and an AVE (Average Variance Extracted) value > 0.5.
   - Discriminant Validity, using cross-loading values (where each indicator had a stronger relationship with its corresponding construct than with other constructs). In addition, the square root of the AVE was compared with the correlations among latent variables, where it should exceed those correlations.
   - Construct Reliability, tested through Composite Reliability (CR) and Cronbach's Alpha with a minimum value of 0.7.

2) *Inner Model Measurement:*
   - Testing the coefficient of determination (R^2) to assess the predictive power of the model.
   - Effect Size testing to determine the magnitude of the effect of independent variables on dependent variables individually.
   - Significance testing of the path coefficient using t-statistic values through a bootstrapping method, with the significance threshold of $t > 1.96$ at a 95% confidence level ($\alpha = 5\%$).
   - Goodness of Fit (GoF) to measure the overall fit of the research model.

To anticipate potential bias in the survey respondents' answers, an additional test was conducted using Harman's single-factor

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test in SPSS, with a threshold of 50% [45]. Therefore, the research stages can be illustrated in the following diagram.

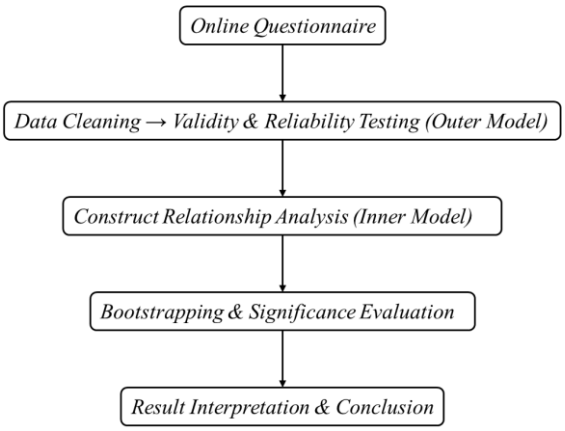

Fig. 2. SmartPLS Analysis Flow Diagram

III. RESULTS AND DISCUSSION

A. Respondent Description

This study involves active student respondents majoring in accounting from several universities in the Jabodetabek area who had an experience in using Large Language Models (LLMs) technology like ChatGPT. The distribution of respondent characteristics is categorized by gender, age, and year of college enrollment. Most respondents are aged 19–21 years, with a male proportion of 33.77% and a female proportion of 66.23%, predominantly consisting of students from the 2023 (33.44%) and 2024 (39.74%) cohorts. Table 1 presents the demographic characteristics of all respondents.

TABLE I. REPONDENTS' CHARACTERISTICS

Item	Category	Frequency	Percentage (%)
Gender	Male	102	33.77
	Female	200	66.23
Age	17	2	0.66
	18	41	13.62
	19	86	28.57
	20	86	28.57
	21	54	17.94
	22	18	5.98
	23	10	3.32
	24	2	0.66
	25	1	0.33
	39	1	0.33
	Missing	1	
Year	2020	1	0.33
	2021	21	6.95
	2022	59	19.54
	2023	101	33.44
	2024	120	39.74

B. Measurement Model Testing Results (Outer Model)

The outer model measurement is conducted to evaluate the validity and reliability of the research indicators through three steps: convergent validity test, discriminant validity test, and construct reliability test.

- Convergent Validity
  The convergent validity test is performed to ensure that all indicators accurately represent the measured variable [43]. The results reveal that all indicators show outer loading values greater than 0.7, signifying that each indicator has a good contribution in measuring its respective construct [44]. Additionally, the Average Variance Extracted (AVE) values for all variables are greater than 0.5, verifying that the model met the criteria for convergent validity [44].

- Discriminant Validity
  Discriminant validity is tested using cross-loading values and the square root of AVE. All indicators showed their highest loading values against the measured construct compared to others, and the square root of AVE for each construct exceeded its correlations with other constructs, thus meeting the criteria for discriminant validity [42].

- Construct Reliability
  Construct reliability is tested using Composite Reliability (CR) and Cronbach's Alpha values, all of which exceeded the minimum value of 0.7. Therefore, all constructs are considered reliable [42]. All variables showed Composite Reliability (CR) and Cronbach's Alpha values greater than 0.7, confirming the questionnaire's reliability and consistency in measuring the investigated variables.

Detailed results of validity and reliability testing can be seen in Table 2: Convergent Validity and Reliability Results.

The measurement model testing results concluded that all indicators meet the required validity and reliability criteria. Therefore, the model is deemed suitable for the inner model measurement.

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TABLE III. CONVERGENT VALIDITY AND RELIABILITY RESULTS

Variable	Code	Indicators	Factor Loadings (> 0.7)	Average Variance Extracted (> 0.5)	Composite Reliability (> 0.7)	Cronbach's Alpha (> 0.7)
Perceived Ease of Use	PEOU1	Easy to Use	0.774	0.642	0.878	0.815
	PEOU2	No Assistance Needed	0.787			
	PEOU3	Less Mental Effort	0.697			
	PEOU4	Clear Interface	0.769			
	PEOU5	Quickly Familiar	0.81			
Perceived Usefulness	PU1	Supports Learning	0.815	0.658	0.906	0.87
	PU2	Information Access	0.808			
	PU3	Boosts Productivity	0.805			
	PU4	Improves Understanding	0.802			
	PU5	Achieve Academic Goals	0.824			
Trust	T1	Data Security	0.737	0.616	0.889	0.844
	T2	Information Transparency	0.827			
	T3	No Misuse	0.798			
	T4	Consistent Response	0.789			
	T5	Accurate Information	0.77			
Academic Ethics	AE1	Idea Generation Only	0.696	0.567	0.84	0.758
	AE2	Verify Information	0.785			
	AE3	Prevent Plagiarism	0.703			
	AE4	Aware of Inacuraccy	0.728			
	AE5	Avoid Copying	0.717			
Behavioral Intention	BI1	Learn New Topics	0.752	0.627	0.893	0.851
	BI2	Continuous Use	0.842			
	BI3	Recommend to Friends	0.82			
	BI4	Help With Difficult Material	0.785			
	BI5	Interest in AI	0.756			
Use Behavior	UB1	Usage Frequency	0.853	0.781	0.914	0.859
	UB2	Use for Assignments	0.923			
	UB3	Rely on for Academic Taks	0.873			

C. Inner Model Measurement

Inner model measurement is conducted through several stages, including testing the determination coefficient (R^2), effect size testing (effect size/f^2), hypothesis testing (path coefficient), and goodness of fit (GoF).

- Determination Coefficient (R^2)
  The adjusted R-square value for the Behavioral Intention variable is 0.619, indicating that the independent variables (Perceived Ease of Use, Perceived Usefulness, Trust, and Academic Ethics) could explain 61.9% of the variation in the Behavioral Intention variable. Meanwhile, the adjusted R-square value for the Use Behavior variable is 0.459, meaning Behavioral Intention can explain 45.9% of the variation in Use Behavior and falls within the moderate category [46].

- Effect Size
  Effect size analysis shows that the impact of Perceived Ease of Use on Behavioral Intention is 0.068 (weak) [47], Perceived Usefulness on Behavioral Intention is 0.265 (moderate) [47], Trust on Behavioral Intention is 0.035 (weak), and Academic Ethics on Behavioral Intention is 0.055 (weak) [47]. Meanwhile, the impact of Behavioral Intention on Use Behavior is 0.855, which was categorized as strong.

- Hypothesis Testing (Path Coefficient)
  Hypothesis testing is conducted using bootstrapping on SmartPLS with criteria values of $t > 1.96$ and p-value < 0.05. The test results show that all paths between variables are statistically significant, thereby

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empirically supporting the five research hypotheses. Specifically:

a) Perceived Ease of Use, Perceived Usefulness, Trust, and Academic Ethics have a positive and significant effect on Behavioral Intention.
b) Behavioral Intention has a positive and significant effect on Use Behavior.

Details of the hypothesis testing results are shown in Table 3: Hypotheses Testing Results.

- Goodness of Fit (GoF)
  The Goodness of Fit (GoF) value of 0.593 indicates that the combined performance of the outer model and inner model in this study falls into the high category [42], thus the model used is appropriate for explaining the phenomenon under study.

TABLE IV. HYPOTHESIS TESTING RESULTS

Hypotheses	Original sample (O)	T statistics (|O/STDEV|)	P values
H1 Perceived Ease of Use -> Behavioral Intention	0.231	4.229	0
H2 Perceived Usefulness -> Behavioral Intention	0.465	8.483	0
H3 Trust -> Behavioral Intention	0.134	3.428	0.001
H4 Academic Ethics -> Behavioral Intention	0.154	3.457	0.001
H5 Behavioral Intention -> Use Behavior	0.679	20.96	0

To assess the potential occurrence of common method bias (CMB) in the survey data, Harman's single-factor test was conducted using exploratory factor analysis in SPSS. All indicators (28 items) from the constructs PEOU, PU, Trust, Academic Ethics, Behavioral Intention, and Use Behavior were entered into the analysis without factor rotation.

As shown in Table 4 on Total Variance Explained and Figure 3 on the Scree Plot, the first factor accounted for 37.15% of the total variance, which is well below the common threshold of 50%. In addition, the Scree Plot revealed a sharp drop after the first component, followed by a gradual slope, indicating that the data contain more than one dominant factor.

Hence, it is proved that common method bias is not a significant issue in this research, and the PLS-SEM analysis results can be interpreted validly.

TABLE V. FACTOR ANALYSIS RESULT

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.401	37.147	37.147	10.401	37.147	37.147
2	2.593	9.260	46.407	2.593	9.260	46.407
3	2.092	7.470	53.878	2.092	7.470	53.878
4	1.340	4.786	58.663	1.340	4.786	58.663
5	1.085	3.875	62.538	1.085	3.875	62.538
6	.947	3.381	65.919			
7	.858	3.063	68.982			
8	.734	2.622	71.604			
9	.673	2.402	74.006			
10	.663	2.368	76.374			
11	.649	2.317	78.691			
12	.557	1.991	80.682			
13	.531	1.898	82.579			
14	.468	1.672	84.251			
15	.458	1.637	85.889			
16	.457	1.632	87.520			
17	.413	1.474	88.994			
18	.398	1.420	90.414			
19	.344	1.229	91.644			
20	.320	1.141	92.785			
21	.313	1.119	93.904			
22	.296	1.059	94.963			
23	.285	1.019	95.982			
24	.254	.908	96.890			
25	.249	.889	97.779			
26	.229	.817	98.596			
27	.207	.740	99.336			
28	.186	.664	100.000			
Extraction Method: Principal Component Analysis.						

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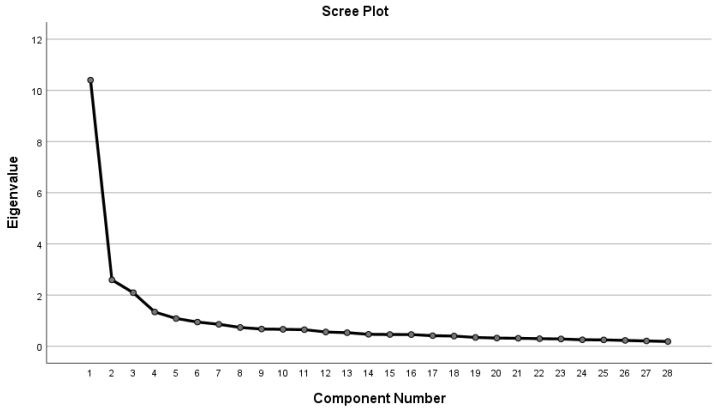

Fig. 3. Scree Plot Result

D. Discussion

The research outcomes generally support the Technology Acceptance Model (TAM) that integrates trust and academic ethics variables. The findings show that perceived usefulness affects behavioral intention, indicating that the greater the benefits students perceive from using LLM technology, the higher their intention to adopt this technology in academic tasks. This is in line with the findings of Refs. [30], [31], [32], who found that perceived usefulness is the main predictor influencing the intention to adopt technology among students.

Perceived ease of use was also found to be significant, indicating that ease of use remains an important consideration. This finding corresponds with the studies of Refs. [22], [26], [27], which shows that PEOU has a significant influence on students' intentions to adopt information technology.

Meanwhile, trust and academic ethics also have a positive influence, indicating that trust in reliability as well as ethical awareness among students also shape their intention to use the technology, although not as strongly as perceived usefulness. These results are consistent with those reported by Refs. [30], [33], [34] emphasize the importance of trust in encouraging the adoption of AI-based technologies such as ChatGPT.

Another important finding is that behavioral intention has proven to be a strong predictor of actual use behavior, meaning that students with a high intention to use LLM technology realize that intention in their real behavior. This is in line with the study by Ref. [30], which highlights the importance of behavioral intention as a bridge to actual behavior.

Overall, the results of this study indicate that the adoption of LLM technology among accounting students is influenced not only by technical factors such as benefits and ease of use, but also by the dimensions of trust and academic ethics. Therefore, educational institutions are advised not only to enhance technological literacy, but also to foster ethical awareness and trust to utilize AI technologies within the academic context.

IV. CONCLUSION

The Partial Least Square-Structural Equation Modeling (PLS-SEM) analysis concluded that there are several predictors that significanlty influence behavioral intention and use behavior of Large Language Models technology among accounting students.

Data analysis using PLS-SEM shows that perceived ease of use, perceived usefulness, trust, and academic ethics strongly predicts students' behavioral intention to adopt Large Language Models technology. Among these four variables, perceived usefulness has the greatest influence, with an effect size of 0.265, indicating that the perceived benefits by students are the main driving force in shaping their intention to use this technology.

Furthermore, behavioral intention significantly predicted use behavior, indicating that the stronger the students' intention to use Large Language Models, the more frequently they apply this technology in learning activities and completing accounting assignments.

Overall, this research model successfully explains the relationships between variables. These findings enhance the understanding of the adoption of Large Language Models (LLMs)-based technology in higher education settings, particularly in the field of accounting.

This study also emphasizes the critical role of formulating clear policies and ethical guidelines regarding the use of LLM technology in academic settings, so that the utilization of this technology can proceed optimally without neglecting aspects of integrity and academic responsibility. The findings obtained may guide the development of policies and pedagogical strategies that are adaptive to technological advancements, while maintaining academic quality and ethics in the era of Artificial Intelligence.

However, this research has several constraints. The study's scope is restricted to accounting students from the Greater Jakarta area (Jabodetabek), potentially hindering the applicability of the findings to other regions or disciplines. In addition, data were collected using self-reported questionnaires, which may introduce perceptual bias. Further research is encouraged to incorporate participants from various study programs and regions across Indonesia and to adopt a mixed-methods approach to develop a more holistic and context-

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sensitive perspective on LLM adoption patterns in higher education.

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