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Analysis of ChatGPT user acceptance among schools in South Tondano District

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ABSTRACT

This study analyzes the relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Behavioral Intention to Use (BI) in the context of educational technology acceptance. The study involved 100 respondents, comprising 80 students and 20 teachers, whose responses were analyzed as a single dataset because both groups evaluated the same technology and research constructs. The proposed model was tested using Partial Least Squares–Structural Equation Modeling (PLS-SEM) to evaluate the measurement model and structural relationships among variables. The measurement model was assessed using factor loadings, the Fornell–Larcker criterion, cross-loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). The structural model and hypotheses were evaluated using bootstrapping in SmartPLS. The findings show that Perceived Ease of Use has a significant positive effect on both Behavioral Intention to Use and Perceived Usefulness, while Perceived Usefulness does not significantly influence Behavioral Intention to Use. These results indicate that ease of use is the primary factor driving technology acceptance among students and teachers. Overall, improving system usability is more effective in promoting technology acceptance than focusing solely on functional benefits. The findings provide practical implications for developers and educational institutions in designing user-friendly educational technologies that meet the needs of both students and teachers.

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INTRODUCTION

In the current digital era, the rapid development of artificial intelligence (AI), particularly conversational AI applications such as ChatGPT, has significantly transformed various sectors, including education (Gill et al., 2024; Muktiarso, 2024). Developed by OpenAI, ChatGPT can generate human-like responses, provide explanations, answer questions, and help users complete various academic and professional tasks. These capabilities have made ChatGPT an increasingly popular educational tool, supporting both learning and teaching activities (Amala et al., 2024). Unlike conventional educational technologies, ChatGPT offers interactive and personalized assistance that can be accessed anytime and anywhere, making it beneficial not only for students but also for teachers in preparing instructional materials, designing learning activities, and improving classroom efficiency (Aisyah et al., 2024). Within the Technology Acceptance Model (TAM), Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are recognized as the two primary factors influencing an individual's intention to adopt new technologies (Wang et al., 2025; Rahmatika & Fajar, 2019). In educational settings, these constructs are relevant for both students and teachers, although they may perceive AI technologies from different perspectives. Students generally utilize ChatGPT to understand course materials, complete assignments, and support independent learning, whereas teachers employ the technology to prepare teaching materials, generate instructional content, and improve the effectiveness of classroom activities. Consequently, understanding technology acceptance requires considering the perspectives of both groups, as they represent the primary users of AI-based educational technologies (Qin et al., 2020).

The increasing adoption of AI in education has become even more prominent following the COVID-19 pandemic, which accelerated the integration of digital technologies into teaching and learning processes (Mhlongo et al., 2023; Lestari & Kurnia, 2023). As educational institutions continue implementing technology-enhanced learning, ChatGPT has emerged as one of the most widely used AI applications due to its ability to provide immediate responses and personalized assistance. For students, ChatGPT facilitates self-directed learning by providing explanations tailored to their level of understanding and helping them solve academic problems more efficiently (Lee et al., 2024; Saputra, 2023). For teachers, the technology reduces the time required to prepare instructional materials, supports lesson planning, and provides alternative approaches for delivering learning content. Previous studies have shown that AI-based technologies improve learning effectiveness, increase engagement, and support educational innovation when they are accepted and appropriately utilized by users (Alimuddin et al., 2023; Jayawardana et al., 2023).

Despite the growing implementation of ChatGPT in education, previous studies have predominantly focused on students' acceptance of educational technologies, while relatively limited attention has been given to examining the combined perspectives of students and teachers within a single technology acceptance model (Dianti et al., 2023; Atin & Lubis, 2017). Since teachers and students interact with the same technology for different educational purposes, understanding their collective perceptions provides a broader perspective on the factors influencing AI adoption in educational environments (Lin & Chen, 2024). Therefore, this study integrates responses from both user groups to investigate how Perceived Ease of Use, Perceived Usefulness, and Behavioral Intention to Use interact in the acceptance of ChatGPT. Academically, this study contributes to extending the application of the Technology Acceptance Model by examining technology acceptance using responses from two important stakeholder groups within education. Practically, the findings are expected to provide valuable insights for educational institutions, teachers, technology developers, and policymakers in designing AI-based educational technologies that are easy to use, useful, and capable of supporting both teaching and learning activities. As suggested by Damayanti & Nuzuli (2023), successful technology implementation requires a comprehensive understanding of users' perceptions and needs. By considering the perspectives of both students and teachers, educational stakeholders can develop more effective strategies to encourage the sustainable adoption of AI technologies in schools.

Accordingly, this study aims to analyze the effect of Perceived Usefulness (PU) on Behavioral Intention to Use (BI), the effect of Perceived Ease of Use (PEOU) on Behavioral Intention to Use (BI), and the effect of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU) in the context of ChatGPT adoption. The study further seeks to provide a comprehensive understanding of technology acceptance among both students and teachers, thereby offering practical recommendations for improving the implementation and utilization of AI technologies in educational settings.

ChatGPT, one of the leading applications in the field of artificial intelligence, offers a text-based interactive platform that simulates human dialogue. This uniqueness makes it extremely useful in educational contexts, where students can easily pose questions and receive answers tailored to their needs. According to Khoir (2024), the implementation of AI-based technology in the education sector not only enhances interactivity but also enables a learning process that is more adapted to individual student needs. This means that ChatGPT does not merely provide information, but also stimulates the development of students' critical thinking skills by encouraging them to explore and consider various perspectives on the subject matter (Gafar, 2024).

Furthermore, the use of ChatGPT in the educational environment holds significant potential to enrich students' learning experiences (Auna & Hamzah, 2024). This tool can be used by students to understand challenging concepts, complete academic tasks, or obtain guidance in exam preparation. Research by Putri & Khasanah (2022) shows that students who leverage AI-based tools like ChatGPT report significant improvements in their comprehension of subject material and engagement in the learning process. With its ability to provide prompt and accurate feedback, ChatGPT can function as a supportive resource for independent learning, not only helping students acquire knowledge but also encouraging them to seek additional information and further exploration.

As an increasing number of students begin to use ChatGPT in their learning processes, it is crucial to conduct further research on how their perceptions of this technology affect their ongoing intention and motivation to use it. Understanding these aspects can provide valuable insights for educators and technology developers, allowing them to create a more effective and supportive learning environment. In this way, an in-depth exploration of the relationship between ChatGPT usage and student learning experiences can help optimize the application of this technology in classrooms, ultimately leading to more innovative and comprehensive teaching approaches.

The Technology Acceptance Model (TAM) is a widely used theoretical framework for analyzing the factors influencing users' acceptance of technology. Developed by Fred Davis in 1989, the model focuses on two primary variables considered to be the main drivers of technology acceptance: Perceived Usefulness (U) and Perceived Ease of Use (PEOU). Perceived Usefulness refers to an individual's belief that using a particular technology will enhance their performance or efficiency in completing specific tasks (Williyanto & Martani, 2023). In the context of education, this implies that students believe tools such as ChatGPT can help them better understand subject material, accelerate the learning process, or even improve academic outcomes.

On the other hand, Perceived Ease of Use describes the degree to which individuals feel comfortable and encounter minimal difficulty when interacting with technology (Dianaris et al., 2022). If students perceive that the technology they use is easy to understand and operate, they are more likely to adopt it in their learning activities (Sayekti & Mardianto, 2019). These two variables interact and contribute directly to Behavioral Intention to Use (BI), which represents an individual's intention to utilize the technology. In other words, if students perceive that ChatGPT is useful and easy to use, they are more likely to integrate it into their study strategies.

In the educational context, TAM provides valuable insights into how students interact with various technologies and how their perceptions of these technologies can influence their intentions to adopt them. Research by Rahmawati & Narsa (2019) indicates that both Perceived Usefulness and Perceived Ease of Use significantly affect students' intention to adopt technology for learning. For instance, students who believe that ChatGPT can enhance their understanding of subject material and expedite the learning process are more inclined to use this tool in their studies. Moreover, students who feel comfortable using ChatGPT tend to recommend it to their peers, which in turn can promote wider adoption among the student population (Auna & Hamzah, 2024).

Beyond understanding the interplay between these two factors, TAM also provides a useful framework for identifying various barriers that students might encounter when trying to adopt new technology. For example, uncertainty or doubt about the effectiveness of a tool may hinder students from embracing it, as they might be concerned that the tool will not deliver the expected results or could even disrupt their learning process. By addressing these elements, educators and technology developers can design better strategies to support technology adoption, such as providing clear information and adequate training to help students feel more confident when using new tools in their learning processes (Amelia, 2023).

Thus, TAM serves not only as an analytical tool but also as a guide for developing strategies that can enhance technology acceptance in educational environments. This is particularly important in today's digital era, where students are confronted with a wide range of tools and technological resources that can enrich their learning experiences. Ensuring that students understand both the benefits and ease of use of technologies like ChatGPT enables educators to create a more inclusive and effective learning environment, where students not only have access to these tools but are also motivated to use them actively.

Although the use of technology in education offers significant benefits, challenges and barriers remain and must be addressed seriously. One major challenge often encountered is the lack of adequate training for both students and educators in utilizing new technologies (Suryawijaya, 2024). In a book by Frandicta et al., (2023), it is highlighted that without effective and comprehensive training, students may feel confused or lack confidence when attempting to use technological tools like ChatGPT. Such uncertainty can hinder their intention to adopt the technology, as they might not fully understand how it works or the benefits it offers.

In addition to training issues, accessibility remains a crucial factor in the implementation of technology in education (Rachmi et al., 2024). Students who do not have adequate access to hardware or a stable internet connection often feel marginalized and cannot fully leverage the potential of advanced technology (Najjar & Oktasari, 2023). This creates a disparity in learning opportunities, where some students benefit from sophisticated technology while others do not. This situation can widen the gap in educational opportunities and is a challenge that stakeholders in the education sector need to address.

Another significant challenge is the concern over data security and privacy. With the increased use of AI-based applications like ChatGPT, there is growing apprehension about how students' personal data is collected, stored, and used (Zakiyah et al., 2024). Research by Putri (2024) indicates that uncertainties regarding data protection may cause students to hesitate in using new technology, fearing that their personal information could be misused or accessed by unauthorized parties. Therefore, it is essential for educational institutions to provide clear and transparent information regarding privacy policies and data security measures. Institutions must also take steps to ensure that students feel safe and protected when using technology in their learning processes (Cahyanto, 2023).

Open and honest communication about these issues is crucial. By providing comprehensive explanations about how their data will be managed and protected, educational institutions can help build trust among students regarding the technology being used. Furthermore, by offering proper training and improved access to devices and internet connectivity, schools and universities can better prepare students to effectively adopt new technology. This approach can overcome existing challenges and barriers, allowing the full potential of technology in education to be realized and utilized by all students.

METHOD

The research model proposed in this study is depicted in Figure 1 and can be described as follows: Hypothesis 1, Perceived Usefulness (U), has a positive effect on Behavioral Intention to Use (BI). In other words, the higher the students' perception of ChatGPT's usefulness, the stronger their intention to use it. Hypothesis 2: Perceived Ease of Use (PEOU) has a positive effect on Behavioral Intention to Use (BI). This indicates that if students find ChatGPT easy to use, their intention to utilize it increases. Hypothesis 3: Perceived Ease of Use (PEOU) has a positive effect on Perceived Usefulness (U). This implies that the easier students find ChatGPT to use, the more beneficial they consider it.

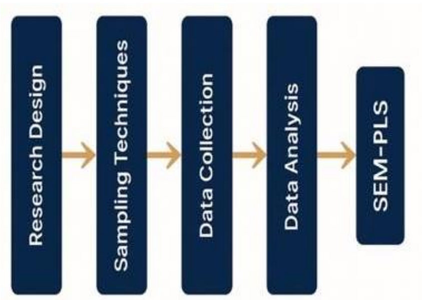

Figure 1. Research Hypothesis Model

A sample refers to a selected subset of the total population that represents the characteristics, attributes, and variability of the population under investigation (Levy & Lemeshow, 2013). By selecting a representative sample, researchers can analyze the collected data and draw conclusions that reflect the broader population. In this study, the sample consisted of 100 respondents, which suggests that the minimum sample size should be at least five times the number of measurement indicators. Since this study employed 20 indicators, a minimum sample of 100 respondents was considered adequate for analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This study employed a purposive sampling technique. Purposive sampling is a non-probability sampling method in which respondents are selected based on specific criteria established by the researcher to ensure that they are relevant to the objectives of the study. The sample comprised 100 respondents, consisting of 80 students and 20 teachers. Although the respondents represented two different user groups, their responses were integrated into a single dataset because both groups had experience using the same educational technology and evaluated the same research constructs. Therefore, the structural model was estimated using the combined responses of students and teachers. The student respondents were selected based on the following criteria: they had experience using the educational technology or learning system examined in this study, had interacted with the system during learning activities, and voluntarily agreed to participate in the research. Meanwhile, the teacher respondents were selected because they had experience using the same educational technology to support teaching and learning activities, had implemented the system in classroom practice, and voluntarily agreed to participate in the study. By applying these selection criteria, both groups of respondents were considered capable of providing reliable and relevant information regarding the acceptance and use of the educational technology investigated in this research.

The questionnaire distribution will be conducted in November 2024, utilizing both online platforms (e.g., Google Forms) and direct meetings. For online data collection, respondents will complete the questionnaire either directly online or through face-to-face meetings with the researcher. The collected responses will be tabulated by variable, and totals will be computed for each respondent. During the data collection process, the researcher will personally contact prospective respondents to seek their consent to participate in the survey. Those who agree will be sent a link to the questionnaire.

Data analysis begins by evaluating the completeness and appropriateness of the data using descriptive statistics in SPSS, ensuring correct data input, an adequate sample size, and that the data conform to the scale used. Structural Equation Modeling (SEM) is then performed using SmartPLS. The analysis involves tests for convergent validity, discriminant validity, and variable reliability. The structural model is tested using PLS Bootstrapping in SmartPLS, which includes significance testing of path coefficients to evaluate the fit of the empirical model to the theoretical model.

RESULTS AND DISCUSSION

Results

The measurement model test results (factor loading) show the validity of the indicators for each construct in this study. The analysis was conducted using a combined dataset of 100 respondents, consisting of 80 students and 20 teachers. The responses from both groups were analyzed simultaneously because they represented the same research model and measurement constructs. Factor loading values were used to assess the extent to which each indicator reflected its corresponding latent variable. According to Hair et al. (2018), a factor loading value of 0.70 or higher indicates acceptable indicator validity. Behavioral Intention to Use (BI) was initially measured using eight indicators (BI1–BI8). Of these, only three indicators (BI1, BI3, and BI7) met the validity criterion, with factor loadings ranging from 0.889 to 0.911. The remaining indicators (BI2, BI4, BI5, BI6, and BI8) were removed because their factor loading values were below the recommended threshold of 0.70.

Perceived Usefulness (PU) was measured using eight indicators (PE1–PE8). Three indicators (PE2, PE6, and PE8) demonstrated satisfactory validity, with factor loadings ranging from 0.880 to 0.902. Among them, PE2 showed the highest loading (0.902). The remaining indicators (PE1, PE3, PE4, PE5, and PE7) were excluded because they did not meet the minimum factor loading requirement. Perceived Ease of Use (PEOU) was measured using eight indicators (PU1–PU8). Six indicators (PU1, PU2, PU4, PU6, PU7, and PU8) met the validity criterion, with factor loadings ranging from 0.709 to 0.887. PU4 showed the strongest loading (0.887), while PU7 had the lowest acceptable loading (0.709). Indicators PU3 and PU5 were removed due to factor loading values below 0.70. Overall, 24 indicators across the three constructs were evaluated. Twelve indicators met the recommended validity criterion and were retained, while the remaining twelve indicators were excluded because their factor loading values were below 0.70. The retained indicators adequately represent their respective latent constructs and were therefore considered appropriate for subsequent structural model analysis.

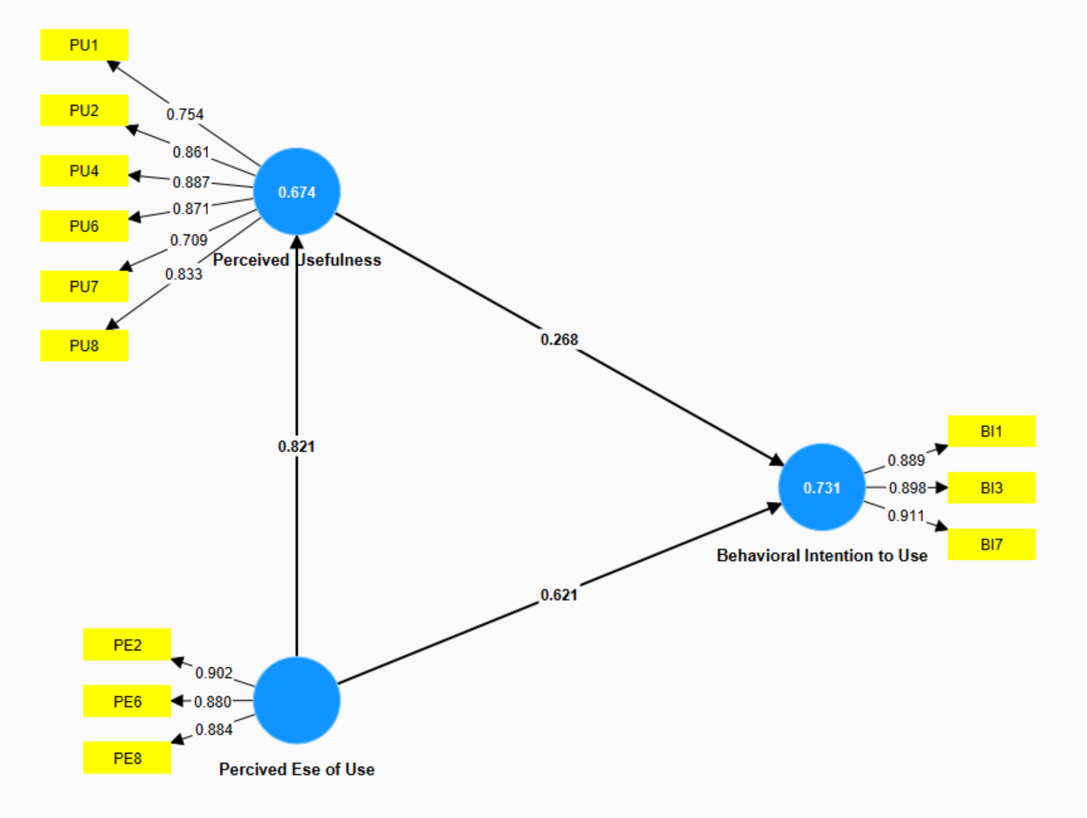

Figure 2. Measurement Model

The Measurement Model Test Result (Factor Loading) Table 1 shows the validity of the indicators for each variable in this study. The factor loading value is used to measure how well the indicator reflects the latent variable. In general, a factor loading value ≥ 0.7 is considered to meet the indicator validity criteria (Hair et al., 2018). Based on the table results, the Behavioral Intention to Use variable is measured using three indicators (BI1, BI3, BI7) with loading values ranging from 0.889 to 0.911, where the BI7 indicator has the highest contribution (0.911). The Perceived Usefulness variable is measured using three indicators (PE2, PE6, PE8), with loading values ranging from 0.880 to 0.902, where the PE2 indicator provides the highest contribution (0.902). The Perceived Ease of Use variable is measured using six indicators (PU1, PU2, PU4, PU6, PU7, PU8) with varying loading values, namely between 0.709 and 0.887. The PU4 indicator has the highest contribution (0.887), while the PU7 indicator shows the lowest contribution (0.709), but still meets the minimum limit of indicator validity.

Overall, all indicators for the tested variables show a factor loading value greater than 0.7, so it can be concluded that these indicators are valid for use in this study. Based on these results, all indicators meet the validity criteria because the factor loading value is greater than 0.7. This shows that these indicators are statistically able to represent their respective latent variables well. This finding confirms the validity of the measurement and supports the feasibility of the model to proceed to structural testing, such as analysis of relationships between latent variables.

Table 1. Measurement Model Test Result (Factor Loading)

No.	Variables	Indicators	Factor Loading
1	Behavioral Intention to Use	BI1	0.889
		BI3	0.898
		BI7	0.911
2	Perceived Usefulness	PE2	0.902
		PE6	0.880
		PE8	0.884
3	Perceived Ease of Use	PU1	0.754
		PU2	0.861
		PU4	0.887
		PU6	0.871
		PU7	0.709
		PU8	0.833

The discriminant validity test in this study was conducted by considering several criteria, including the Fornell-Larcker Criterion and cross-loading. In the Fornell-Larcker Criterion validity test, the first step is to compare the square root of the Average Variance Extracted (AVE) for each variable with the correlation between variables in the model. Discriminant validity is considered fulfilled if the square root value of AVE is greater than the correlation between different variables. Table 2 presents the results of the Fornell-Larcker Criterion validity test, with the correlation values between variables located outside the diagonal of the table, and the square root of AVE located on the diagonal. Each value on the diagonal indicates the square root of AVE for each variable, which must be greater than the correlation value between other variables located in the corresponding position. Analysis of the table results shows that all variables in the model have a higher AVE square root value compared to the correlation between latent variables. For example, for the Behavioral Intention to Use (BI) variable, the AVE square root value of 0.899 is greater than the correlation with other variables, namely Perceived Effectiveness (PU) (0.778) and Perceived Ease of Use (PEOU) (0.841). Likewise, the Perceived Effectiveness (PU) variable has an AVE square root value of 0.822, which is higher than the correlation between other variables, namely Behavioral Intention to Use (BI) (0.778) and Perceived Ease of Use (PEOU) (0.821). In addition, the Perceived Ease of Use (PEOU) variable has an AVE square root value of 0.889, which is also higher than the correlations with Behavioral Intention to Use (BI) (0.841) and Perceived Usefulness (PU) (0.821).

Overall, the results of the analysis show that each variable in the model has a square root value of AVE greater than the correlation between variables, indicating that discriminant validity has been met. Thus, this model meets the Fornell-Larcker criterion and can be considered valid in terms of discrimination between the variables tested.

Table 2. Fornell-Larcker Criterion

No.	Variables	1	2	3
1	Behavioral Intention to Use	0.899		
2	Perceived Usefulness	0.778	0.822	
3	Perceived Ease of Use	0.841	0.821	0.889

All indicators meet the requirements, considering that their correlation with the intended construct is greater than with other constructs in the model. In addition, the cross-loading value of each indicator is higher against the intended construct compared to other constructs, as shown by the data in Table 3. This indicates that each indicator predominantly measures the intended construct, which reflects good measurement validity.

Table 3. Cross Loading

No.	Indicators	Behavioral Intention to Use	Perceived Usefulness	Perceived Ease of Use
1	BI1	0.889	0.696	0.711
2	BI3	0.898	0.746	0.815
3	BI7	0.911	0.651	0.736
4	PE2	0.715	0.765	0.902
5	PE6	0.782	0.724	0.880
6	PE8	0.744	0.699	0.884
7	PU1	0.428	0.754	0.513
8	PU2	0.722	0.861	0.774
9	PU4	0.711	0.887	0.760
10	PU6	0.745	0.871	0.777
11	PU7	0.393	0.709	0.426
12	PU8	0.698	0.833	0.674

These results indicate that each indicator has the highest loading value on the latent variable that should be measured. For example, indicator BI1 has the highest loading value on the Behavioral Intention to Use variable (0.889) compared to its correlation with other variables such as Perceived Usefulness (0.696) or Perceived Ease of Use (0.711). The same applies to other indicators, such as BI3, which has the highest loading value on Behavioral Intention to Use (0.898), and BI7, which has the highest loading value on Behavioral Intention to Use (0.911). On the Perceived Usefulness variable, indicator PE2 has the highest loading value on this variable (0.765), which is greater than its correlation with other variables, such as Behavioral Intention to Use (0.715) or Perceived Ease of Use (0.902). Likewise, for the PE6 indicator, which has the highest loading value on Perceived Usefulness (0.782), compared to its correlation with other variables such as Behavioral Intention to Use (0.746) or Perceived Ease of Use (0.880). The PE8 indicator also shows the highest loading value on Perceived Usefulness (0.744) compared to its correlation with other variables, such as Behavioral Intention to Use (0.651) and Perceived Ease of Use (0.884). In the Perceived Ease of Use variable, the PU2 indicator has the highest loading value on this variable (0.861), which is higher than its correlation with Behavioral Intention to Use (0.722) or Perceived Usefulness (0.774). Indicators PU4 and PU6 also showed the highest loading values on Perceived Ease of Use with loading values of 0.887 and 0.871, respectively, which were greater than their correlations with other variables such as Behavioral Intention to Use (0.711–0.745) and Perceived Usefulness (0.887–0.777). Overall, these results indicate that the indicators in each variable are more correlated with the corresponding latent variables, indicating good validity in measuring each variable.

The reliability test of the variables in this study was conducted by analyzing the Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) values. A variable is considered reliable if the Cronbach's alpha value is more than 0.7, the composite reliability is above 0.70, and the AVE reaches a minimum value of 0.50. The results of the reliability and construct validity tests show that all variables in this study have good levels of reliability and validity. In the Behavioral Intention to Use variable, the Cronbach's Alpha value is 0.882, and the rho_A value is 0.885, indicating good internal consistency. The composite reliability for this variable is 0.927, which is greater than the threshold value of 0.70, indicating very good construct reliability. In addition, the AVE value for this variable is 0.809, which is higher than the minimum value of 0.50, indicating good convergent validity. For the Perceived Usefulness variable, the Cronbach's Alpha value is 0.905, and the rho_A value is 0.926, indicating very good internal reliability. The composite reliability value is 0.925, which also indicates high construct reliability. However, the AVE value for this variable is 0.675, which is slightly lower than the threshold of 0.7, although it is still acceptable in some research contexts. Meanwhile, in the Perceived Ease of Use variable, the Cronbach's Alpha value is 0.867 and rho_A is 0.867, indicating good internal reliability. The composite reliability value of 0.918 indicates strong construct reliability. The AVE for this variable is 0.789, which is greater than 0.50, indicating that most of the indicator variance can be explained by the construct.

Overall, the results of the reliability and validity tests of this construct indicate that all variables in this study have good reliability and adequate validity. The variables Behavioral Intention to Use, Perceived Usefulness, and Perceived Ease of Use meet the expected reliability and convergent validity criteria, indicating that the constructs measured in this study can be trusted for use in further analysis. These results indicate that all constructs in this study meet strong reliability and validity criteria, so they can be used for further analysis.

Table 4. Result of the Reliability Testing

No.	Variables	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)	Description
1	Behavioral Intention to Use	0.882	0.885	0.927	0.809	Reliable
2	Perceived Usefulness	0.905	0.926	0.925	0.675	Reliable
3	Perceived Ease of Use	0.867	0.867	0.918	0.789	Reliable

Based on the results shown in Table 4, each indicator shows a value that exceeds the recommended minimum limit. The reliability test of the variables shows that the Cronbach's alpha value for all variables is more than 0.70, the composite reliability is above 0.70, and the AVE exceeds 0.50. Thus, it can be concluded that the reliability of all variables in this study is good.

Table 5. R-Square

No.	Variables	R-square
1	Behavioral Intention to Use	0.731
2	Perceived Usefulness	0.674

The R-square (R^2) analysis can be seen in Table 5, where the Behavioral Intention to Use variable can be explained by 73.1%, indicating a strong influence. This means that most of the variation in Behavioral Intention to Use can be explained by other variables in the model. While Perceived Usefulness can be explained by 67.4%, which also shows a significant influence, although slightly lower. Overall, this R^2 value shows that the model has good predictive power with a strong contribution from the variables in explaining the variation of the two variables.

Table 6. F-Square

No.	Varibles	Behavioral Intention to Use	Perceived Usefulness	Perceived Ease of Use
1	Behavioral Intention to Use			
2	Perceived Usefulness	0.087		
3	Perceived Ease of Use	0.467	2.069	

f^2 (f-square) is a measure used to measure the strength of the influence between two variables in a structural model, such as in PLS-SEM analysis. The f^2 value indicates how much of a change in the dependent variable can be explained by a change in the independent variable. I use a common interpretation for the f^2 value: if the value is less than 0.02, the influence is considered very small; between 0.02 and 0.15, the influence is small; and more than 0.15, the influence is large. Based on the results obtained, the influence between the variables in this study is mostly small. The influence between Behavioral Intention to Use and Perceived Usefulness of 0.087 indicates a very small influence. Meanwhile, the influence between Behavioral Intention to Use and Perceived Ease of Use is 0.467, which indicates a small to moderate influence. The influence between Perceived Usefulness and Perceived Ease of Use is much greater, with an f^2 value of 2.069, which indicates a large influence. Overall, although most of the influences found were small, the relationship between Perceived Usefulness and Perceived Ease of Use showed a significant influence in this model.

After testing the validity and reliability at the measurement model stage and ensuring that all indicators meet the established standards, the next step is to conduct structural model testing. At this stage, the main objective is to test the validity of each hypothesis in the study. Structural model testing, or hypothesis testing, is done by evaluating the significance of the path coefficients using the PLS Bootstrapping method through SmartPLS statistical software. The results of this structural model testing are presented in Figure 3 and Table 7.

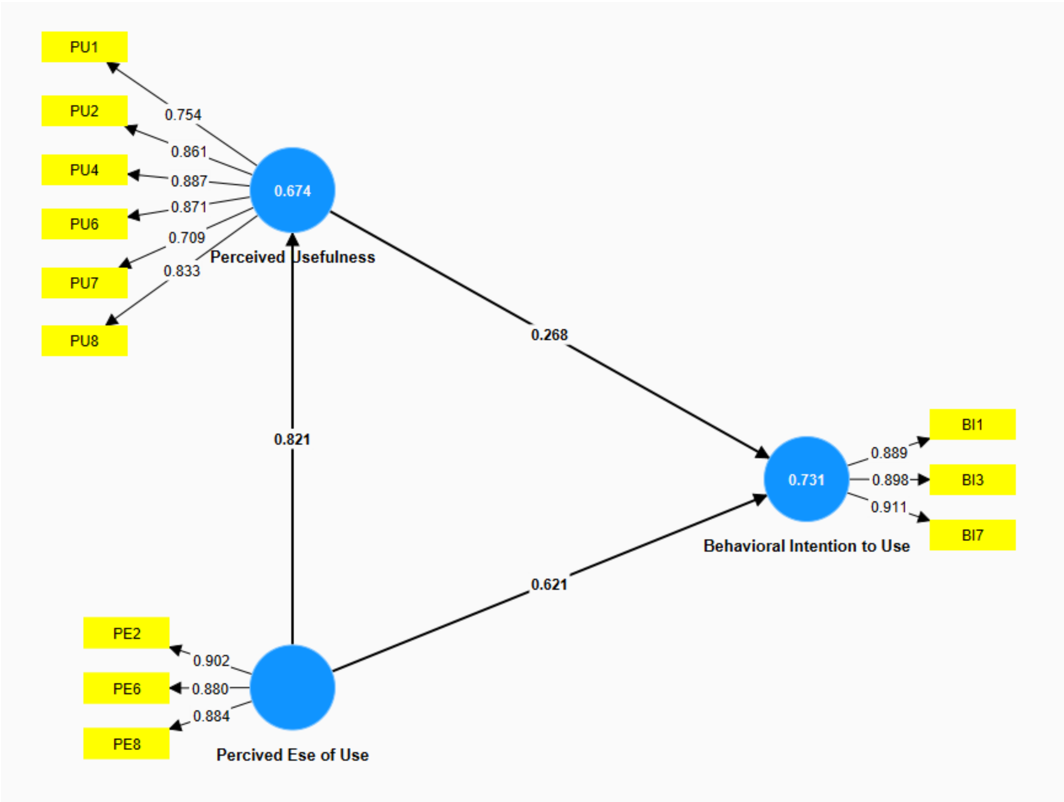

Figure 3. Results of the Structural Models PLS Bootstrapping

Table 7. Results of Hypothesis Testing of Structural Models

Variables	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Significant?
Perceived Usefulness -> Behavioral Intention to Use	0.295	0.174	1.542	0.123	No
Perceived Ease of Use -> Behavioral Intention to Use	0.837	0.042	20.049	0.000	Yes
Perceived Ease of Use -> Perceived Usefulness	0.824	0.049	16.751	0.000	Yes

Discussion

This study aims to examine the relationships among Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention to Use (BI) using the Technology Acceptance Model (TAM). The structural model was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with SmartPLS software. The analysis was conducted using a combined dataset of 100 respondents, consisting of 80 students and 20 teachers. Since both respondent groups evaluated the same technology and measurement constructs, their responses were analyzed together in a single structural model. Therefore, the hypothesis testing reflects the overall perceptions of all respondents rather than separate statistical results for students and teachers.

The first hypothesis examined the influence of Perceived Usefulness (PU) on Behavioral Intention to Use (BI). The analysis produced a t-statistic of 1.542 with a p-value of 0.123, which is greater than the significance threshold of 0.05. Therefore, the first hypothesis is not supported, indicating that Perceived Usefulness does not significantly influence Behavioral Intention to Use. Although the Technology Acceptance Model suggests that users are more likely to adopt a technology when they perceive it as useful (Ma & Liu, 2005; Kumala et al., 2020), the findings of this study indicate that perceived usefulness alone is insufficient to increase users' intention to use the system (Alkhawaja, 2022). Considering the characteristics of the respondents, students are generally familiar with digital technologies in their learning activities, while teachers tend to focus on whether the technology effectively supports instructional tasks (Sayaf et al., 2022). When both perspectives are combined, the perceived usefulness of the system may no longer become the primary factor influencing behavioral intention. This finding is consistent with previous studies by Febrian & Ahluwalia (2020) and Sutisna & Sutrisna (2023), which reported that the effect of Perceived Usefulness on Behavioral Intention to Use varies depending on the characteristics of users, technology experience, and the implementation context.

The second hypothesis examined the influence of Perceived Ease of Use (PEOU) on Behavioral Intention to Use (BI). The results show a t-statistic of 20.049 with a p-value of 0.000, indicating a statistically significant positive relationship. Thus, the second hypothesis is accepted. This finding suggests that the easier respondents perceive the technology to be, the stronger their intention to use it. For students, an easy-to-use system enables them to complete learning activities more efficiently without requiring extensive technical knowledge (Zainuddin, 2024). Likewise, teachers are more willing to adopt technology when it can be operated with minimal effort and integrated smoothly into teaching activities (Mehdaoui, 2024). Although the statistical analysis was conducted using a combined dataset, these findings indicate that ease of use is an important consideration for both respondent groups. This result supports the Technology Acceptance Model and is consistent with previous studies conducted by Putri et al., (2021), Putra & Raharjo (2022), and Ashsifa (2020), all of which concluded that Perceived Ease of Use is one of the strongest determinants of technology adoption.

The third hypothesis investigated the influence of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU). The analysis generated a t-statistic of 16.751 with a p-value of 0.000, indicating a significant positive relationship. Therefore, the third hypothesis is supported. The findings imply that respondents perceive technologies that are easier to operate as being more useful in accomplishing their tasks. From the students' perspective, systems that are easy to use simplify learning activities and improve productivity (Silva et al., 2022). From the teachers' perspective, user-friendly technologies facilitate lesson preparation, classroom management, and instructional delivery, thereby increasing the perceived benefits of the system (Álvarez et al., 2024). Although these interpretations describe the possible perspectives of students and teachers, the statistical evidence represents the combined responses of both groups because the structural model was estimated using a single integrated dataset. These findings are consistent with the original Technology Acceptance Model and supported by previous studies by Ardianto et al., (2021), Sutisna & Sutrisna (2023), and Zahara & Amalia (2024), which reported that Perceived Ease of Use significantly enhances Perceived Usefulness.

Overall, the hypothesis testing demonstrates that Perceived Ease of Use is the most influential construct in the proposed model. It has a significant positive effect on both Behavioral Intention to Use and Perceived Usefulness, whereas Perceived Usefulness does not significantly influence Behavioral Intention to Use. These findings indicate that respondents, regardless of whether they are students or teachers, place greater importance on the ease of using the technology than on its perceived functional benefits when deciding whether to adopt it. Consequently, improving system usability is likely to be a more effective strategy for increasing technology acceptance than focusing solely on enhancing its functionality.

CONCLUSION

Based on the results of the structural model testing and hypothesis analysis, this study concludes that Perceived Ease of Use (PEOU) is the most influential factor affecting both Behavioral Intention to Use (BI) and Perceived Usefulness (PU). Conversely, Perceived Usefulness does not have a significant effect on Behavioral Intention to Use, indicating that the perceived benefits of the technology alone are insufficient to encourage users' intention to adopt it. These findings suggest that users are more likely to accept and continue using a technology when it is easy to understand, operate, and integrate into their daily activities. From the students' perspective, the findings imply that technology adoption is primarily driven by ease of use. Students tend to develop stronger intentions to use a learning system when it is intuitive, accessible, and requires minimal effort to operate. Therefore, educational technology developers should prioritize user-friendly interfaces, clear navigation, and simple interaction processes to improve students' learning experiences and encourage continuous system use. From the teachers' perspective, the results indicate that ease of use also plays a critical role in technology adoption. Teachers are more likely to integrate digital technologies into their teaching practices when the systems are easy to learn, require minimal technical support, and can be implemented efficiently in classroom activities. Although the perceived usefulness of the technology remains important, the findings suggest that practical usability is a stronger determinant of teachers' intention to adopt educational technologies. Consequently, training programs and system development should emphasize simplicity, accessibility, and operational efficiency to support technology acceptance among teachers.

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