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Technology Acceptance Model for Reconstructing Al-Islam and Kemuhammadiyah Learning at Universitas Muhammadiyah Sumatera Utara

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Abstract

This study aims to see the influence of Usability Perception, Ease of Use, Attitude, and Behavioral Intention on Technology-Based AIK Learning in Universitas Muhammadiyah Sumatera Utara. Technology is currently an indicator of the development of science. Currently, Universitas Muhammadiyah Sumatera Utara continues to try to develop technology-based learning media towards a world-class university. However, many students are still not maximized with running the technology prepared for teaching, especially in AIK courses. This study uses a quantitative approach, hypothesis testing, and the inner model obtained from data processing using SMART PLS. The conclusion are this study the t-statistic value for variable X1 (perceived usefulness) indicates that perceived convenience does not affect technology-based AIK learning, and the t-statistic value for variable X2 (Ease of Use) indicates that ease of use does not affect technology-based AIK learning. So, the t-statistic value for variable X3 (Attitude) indicates that attitude affects technology-based AIK learning. The t-statistic value for variable X4 (Behavioral Intention) indicates that Behavioral Intention affects technology-based AIK learning. The Technology Acceptance Model (TAM) explains how users accept and adopt technology based on two main factors: perceived usefulness and perceived ease of use. In the context of AIK learning at Universitas Muhammadiyah Sumatera Utara (UMSU), TAM plays a crucial role in shaping the effectiveness and efficiency of technology-based learning.

Keywords AIK; Digital Learning; Technology Acceptance Model

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1. INTRODUCTION

The development of digital technology in the world of education is currently experiencing a significant increase, which can be seen from the number of educational institutions that use digital platforms in the teaching process; This development began since the Covid 19 outbreak that occurred in Indonesia, where Indonesian people were asked to Social Distancing in various activities, including in teaching activities. As time goes by, digital-based teaching continues to be developed in every educational institution, especially now with digital platforms used in teaching, which can make it easier for teachers and students (Saikat, 2021). One of the institutions that continues to develop digital

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platforms in education is Universitas Muhammadiyah Sumatera Utara. The teaching system applied at UMSU adheres to blended learning, where there is both offline and online teaching. Currently, UMSU continues to innovate learning to realize a world-class university. To become a world-class university, UMSU must have a digital platform in the online teaching system. Not only that, UMSU must also provide digital-based learning media, so that students can receive or absorb the material provided properly.

Developing a digital platform in the teaching system carried out at UMSU is not easy. Of course, many challenges must be faced, from training teaching staff, to socializing students in running the digital platform provided by UMSU in the teaching process. At present, there are still many students who are reluctant to do online learning, because according to them, learning with a digital system is more difficult than a face-to-face or direct learning system (Mpungose, 2020)(Lampropoulos, 2022)(Chassiakos, 2020)(Mazaheri, 2020). This can be seen from the small number of students who access the digital learning platform provided by UMSU, which the Digital-based Learning Technical Implementation Unit will evaluate each semester. It can be seen from the evaluation that most students did not access the platform provided by UMSU, especially in the Al-Islam and Kemuhammadiyahan subjects. In the evaluation, there was no exposure to the obstacles faced by students in accessing the digital learning platform. For this reason, researchers try to construct a Technology Acceptance Model to offer a comprehensive model that will later explain students' driving and inhibiting factors in using the digital learning system provided by UMSU. This research will also be able to see and find solutions to realize a world-class university at UMSU. The research conducted will also support the Sustainable Development Goals (SDGs) program, specifically regarding Quality Education in building qualified human resources.

This research will construct the Technology Acceptance Model theory to find the driving and inhibiting factors in implementing digital-based learning, especially in the Al-Islam and Muhammadiyah (AIK) courses at the Muhammadiyah University of North Sumatera. This research will also become reference material in realizing a world-class university at the Muhammadiyah University of North Sumatera. In this research, the researcher carried out research mapping using Publish or Perish, then specified using VosViewer, and the researcher only focused on journal references indexed by Scopus. The results from VosViewer are as follows:

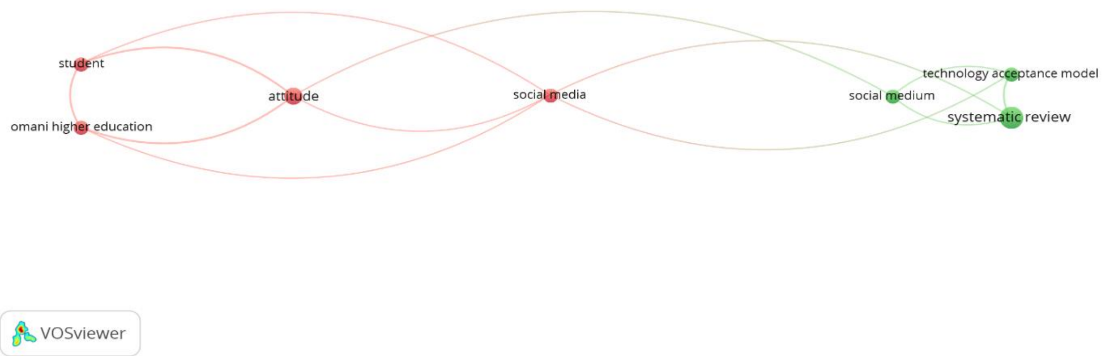

Figure 1. Results of Scopus Indexing Research Mapping 2019-2024

The image above shows a study that discusses *the Technology Acceptance Model* in the digital learning system. The dot is green, which means that this research is still rarely done, so the researcher is trying to construct a Technology Acceptance Model to see and find solutions in realizing *a world-class* *university* at the University of Muhammadiyah North Sumatera. The results of the mapping at AATS explain several research themes that are often carried out, Student (Habes, 2020) (Marbán, 2021) (Osipovskaya, 2020) (Al-Qaysi, 2019), Oman Higher Education (Al-Qaysi, 2020) (Al-Qaysi, 2019), Attitude (Lampropoulos, 2022)(Feldman, 2021)(Hermita et al., 2019), Social Media (Ducange, 2019) (Nickerson, 2019) (Kapoor, 2022) (Cepeda-Carrion, 2023) (Reisach, 2021) (Polanco-Levicán, 2022) (Muftah, 2023) (Lee, 2022), Social Medium (J. T. Wong & Hughes, 2023), Technology Acceptance Model (Al-Maroof, 2022) (Hermita et al., 2019) (Surameery & Shakor, 2021), Systematic Review (Polanco-Levicán, 2022) (Beer, 2021) (Jahan, 2023) (Al-Qaysi, 2023) (Al-Maroof, 2022) (Saikat, 2021). The research that is the reference material is as follows:

Noor, Andriana, Mustafa, Ramayah, Edwin, and Tugrul have published the results of the study in 2023 (Al-Qaysi, 2023) With the title "*Social Media Adoption In Education: A Systematic Review Of Disciplines, Applications, and Influential Factors," This research discusses digital-based learning media by involving social media and also constructs the theory of the Technology Acceptance Model*. The results are that digital-based learning can provide quick understanding, and adopting digital learning media is also the most important thing in accelerating students' understanding. This study also discusses social media often used in learning, as the research finds that the social media used in the digital learning system is Facebook. This research differs from the research conducted, where the learning seen in the previous research involved electronic media, as a learning process in finding references. In contrast, the research involved the platform owned by the campus.

Surameery and Shakor published the results of their research in 2021 with the title "CBES: Cloud-Based Learning Management System For Educational Institutions." This research outlines how digital-based learning must be carried out in every educational institution, due to the increasing development of technology. The research results are that cloud-based learning is very effective to implement, and can improve students' understanding related to learning (Surameery & Shakor, 2021). This research differs from the research that will be conducted, where the previous research used the variables of understanding. In contrast, the variables used in this study are perception of usefulness, ease, attitude, and behavior intention.

Rana, Noor, Said, and Mostafa published a study in 2021, entitled "*Blended Learning Acceptance: A Systematic Review Of Information System Models*" This study uses a review literature system, where the researcher maps the research with a discussion of blended learning, and the results obtained, that learning with e-learning is the most effective tool used in classroom management (Al-Maroof, 2022). In previous research, the method used was qualitative research, while the research used quantitative research.

Josep and Brandley published a study in 2022 titled "Leveraging Learning Experience Design: Digital Media Approaches to Influence Motivational Traits That Support Student Learning Behaviors in Undergraduate Online Courses." This research uses a quantitative approach, involving digital media in motivating students to be active in learning. The results obtained are that digital learning media have a positive effect on learning motivation, and of course, affect students' ability to learn in the classroom (J. T. Wong & Hughes, 2023). This research is similar to the research on digital learning; the variables used differ from the research conducted.

Matrissya, Farida, Eko, and Robie published the results of a study in 2019 entitled "The Determinants and Impact of System Usage and Satisfaction on E-Learning Success and Faculty-Student Interaction in Indonesian Private Universities." The research used a quantitative approach, with SEM analysis. The results showed that all variables had sufficient model compatibility. In contrast, the structure model revealed that seven out of nine hypotheses were significant, including the e-learning system affecting user satisfaction (Hermita et al., 2019). Previous research has a difference from the previous research in that the previous research used structural variables that are considered to mediate in influencing satisfaction. In contrast, in this study, the *Technology Acceptance Model* was used to see the influence of the digital learning system.

2. METHODS

This study uses a quantitative approach, with hypothesis testing, and the inner model obtained from data processing using SMART PLS (Akrim et al., 2022) (Mart & Mart, 2021) (Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, 2021). The advantages of SMART PLS can display a comprehensive model, along with its ability to confirm the dimensions of a construct or factor and measure the influence of theoretical relationships. SMART PLS is also a combination of confirmatory factor analysis and regression analysis. The sample used in this study was 527 people who met the criteria for lift distribution. The distribution of the questionnaire to students, by providing a Google form link containing a statement, then students give answers according to what has been given. After collecting the data, the next step is processing using the SmartPLS (Partial Least Squares) application. SmartPLS is a software specifically designed for Structural Equation Modeling (SEM) analysis, which allows researchers to test the relationship between variables simultaneously.

a. Measurement Model: First, the researcher builds a measurement model that describes the relationship between the indicator and the construct. At this stage, the validity and reliability of the measuring tool are tested using confirmatory analysis.

b. Structural Model: Next, structural models are built to explore the relationship between independent variables and dependent variables. The researcher used the path coefficient to assess the strength and direction of the relationship between the variables.

c. Hypothesis Test: Hypothesis testing is carried out to determine whether there is a significant influence between independent and dependent variables. The analysis results will show the p- and t-statistic values used to test the significance of the hypothesis.

Result Interpretation: The results obtained from SmartPLS will be interpreted and presented as tables and graphs to make it easier to understand. Researchers will discuss these findings in the context of educational theory and practice and provide recommendations based on the research results.

3. FINDINGS AND DISCUSSIONS

Findings

Model Instrument Validity Testing

a. Convergent Validity Testing

Convergent validity testing is carried out to determine the suitability or correctness of each instrument in measuring the research construct variable. An instrument that has a good validity value is an instrument that is suitable and appropriate to use to measure the construct variable. The first convergent validity test is to see the loading factor value of each instrument on the construct variable. A loading value greater than 0.7 is a good loading factor value for the instrument to measure the construct variable. The results of the loading factor of each instrument on the construct variable can be seen in the following figure.

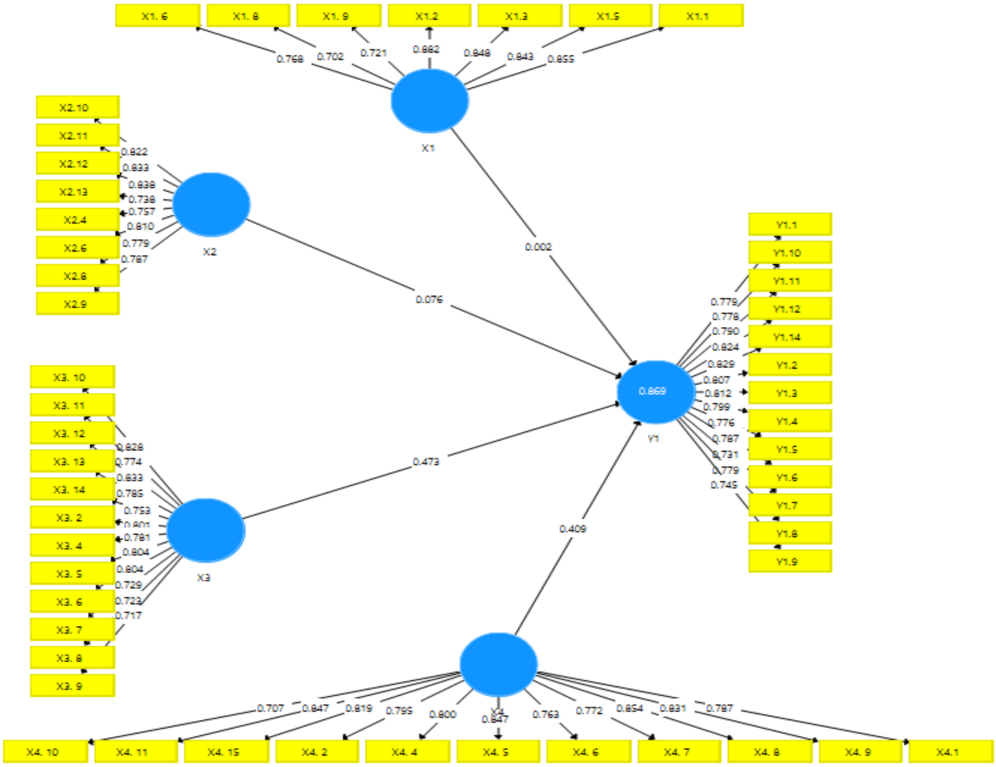

Figure 2. Loading Factor Results

In the figure, the loading factor value of each instrument on the construct variable is greater than 0.7. Thus, it can be concluded that convergent validity testing with the loading factor approach has been fulfilled; in other words, the construct variable instruments in the study are valid. Furthermore, the second convergent validity test is to see the Average Variance Extracted value on the construct variable. An Average Variance Extracted value greater than 0.5 is a good Average Variance Extracted value for the construct variable. The results of this convergent validity test are explained as follows: The validity test is carried out to determine whether a questionnaire is correct or valid. A measuring instrument can be declared high validity if the tool performs its measuring task for the measurement.

Table 1. Validity Test

	X1	X2	X3	X4	Y1	AVE
X1.1	0,855					**0,649**
X1.2	0,882					
X1.3	0,848					
X1.5	0,843					
X1. 6	0,768					
X1. 8	0,702					
X1. 9	0,721					
X2.4		0,757				0,634
X2.6		0,810				
X2.8		0,779				
X2.9		0,787				

	X1	X2	X3	X4	Y1	AVE
X2.10		0,822				
X2.11		0,833				
X2.12		0,838				
X2.13		0,738				
X3. 2			0,801			0,606
X3. 4			0,781			
X3. 5			0,804			
X3. 6			0,804			
X3. 7			0,729			
X3. 8			0,723			
X3. 9			0,717			
X3. 10			0,828			
X3. 11			0,774			
X3. 12			0,833			
X3. 13			0,785			
X3. 14			0,753			
X4.1				0,787		0,645
X4. 2				0,795		
X4. 4				0,800		
X4. 5				0,847		
X4. 6				0,763		
X4. 7				0,772		
X4. 8				0,854		
X4. 9				0,831		
X4. 10				0,707		
X4. 11				0,847		
X4. 15				0,819		
Y1.1					0,779	0,621
Y1.2					0,807	
Y1.3					0,812	
Y1.4					0,799	

	X1	X2	X3	X4	Y1	AVE
Y1.5					0,776	
Y1.6					0,787	
Y1.7					0,731	
Y1.8					0,779	
Y1.9					0,745	
Y1.10					0,778	
Y1.11					0,790	
Y1.12					0,824	
Y1.14					0,829	

The table above shows that the Average Variance Extracted value of all construct variables in this study is greater than 0.5 (AVE> 0.05). Thus, it can be concluded that all construct variable instruments used in this study have met the criteria for convergent validity testing. None of the instruments were deleted from the construct variables in this study.

Discriminant Validity Testing Fornell-Larcker Approach

Discriminant validity testing aims to see whether the instrument used in one construct variable differs from that used in other variables. So conceptually, it is hoped that the instrument used can measure the variable it is measuring and is different from the instruments on other variables. Discriminant validity testing uses the Fornell-Larcker Criterion and Cross-Loading techniques. The Fornell-Larcker Criterion postulate states that discriminant validity can be good if the Average Variance Extracted root value is higher when compared to the correlation value of other construct variables. Meanwhile, another discriminant validity test uses cross-loading, where discriminant validity is said to be good if the instrument value of the construct variable is higher than the instrument value on other construct variables. Thus, the Fornell-Larcker Criterion tests the construct variable, while cross-loading is in the construct variable instrument. The results of discriminant validity testing in this study can be seen in the following table:

Table 2. Discriminant Validity

	X1	X2	X3	X4	Y1
X1	0,806				
X2	0,813	0,796			
X3	0,820	0,871	0,779		
X4	0,768	0,805	0,925	0,803	
Y1	0,765	0,818	0,918	0,909	0,788

The table above shows that the matrix correlation value of the construct variable itself is greater than the matrix value of the construct variable with other constructs. It is known that the matrix correlation value, which is 0.806, is greater than the matrix correlation value of the feedback technology-based AIK learning construct variable with other construct variables. Likewise, the same results are shown in the correlation matrix of variable X1, which is 0.806. The correlation matrix value of variable X2 is 0.796 the correlation matrix value of variable X3 is 0.803. The matrix values on these construct variables are greater than the correlation matrix values of the construct variables with other construct variables.

Reliability Test

Reliability is a tool to measure a questionnaire, an indicator of variables or constructs. A questionnaire is declared reliable or reliable if the individual's answer to the statement is consistent or stable over time. A variable or construct can be declared reliable if it provides a Cronbach's alpha value> 0.70.

Table 3. Cronbach Alpha Value

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
X1	0,908	0,916	0,928	0,649
X2	0,917	0,920	0,933	0,634
X3	0,941	0,942	0,949	0,606
X4	0,945	0,947	0,952	0,645
Y1	0,949	0,950	0,955	0,621

The table above shows that the Cronbach's alpha value is above 0.70, meaning all instruments are declared reliable in this study.

This means that all instruments are declared reliable.

Structural Equation Modeling Analysis (Inner Model)

a. Predictive Relevance

Predictive Relevance measures how well the observations made provide results on the research model. The Predictive Relevance (Q2) value ranges from 0 (zero) to 1 (one); the closer to 0 the Predictive Relevance (Q2) value is, indicating that the research model is getting worse. On the contrary, the further away from 0 (zero) and the closer to the value of 1 (one), the means the research model is getting better (Maryani et al., 2020).

Table 4. Construct Cross-Validated Redundancy

	SSO	SSE	Q^2 (=1-SSE/SSO)
X1	1400,000	1400,000	
X2	1600,000	1600,000	
X3	2400,000	2400,000	
X4	2200,000	2200,000	
Y1	2600,000	1221,031	0,530

The table above shows that in this study, the Predictive Relevance (Q2) value is 0.5230, meaning that in this study, the research model is getting better because it is getting closer to the value of 1 (one).

Model Fit Testing

Before analyzing Structural Equation Modeling - Partial Least Squares (SEM-PLS), testing whether the model used in this study is in a fit or non-fit position is necessary. Measuring a model's fit can use the Standardized Root Mean Square (SRMR) value. The model is declared fit if the SRMR value is smaller than 0.08. The results of this fit model test can be seen from the following table.

Table 5. Model Fit

	Saturated Model	Estimated Model
SUMMER	0,075	0,075
d_ULS	7,530	7,530
d_G	10,541	10,541
Chi-Square	7094,163	7094,163
NFI	0,518	0,518

The table above shows that the fit model matches the data in the research because the SRMR value is <0.1 above and the NFI is below 0.08 and close to 0.518.

Rsquare

The coefficient of determination determines how much the model can explain the dependent variable. If the coefficient of determination (R2) is getting bigger or closer to 1, it can be said that the independent variable (X) is large on the dependent variable (Y). This means the model is getting stronger in explaining the effect of the independent variables studied on the dependent variable.

Table 6. R Square

	R Square	R Square Adjusted
Y1	0,869	0,866

The table above shows the coefficient of determination (R2) of 0.869 or 86.9%, indicating a very strong ability of the independent variables: Perceived Usefulness, Ease of Use, Attitude, and Perpetrator Intention on Technology-based AIK Learning. The remaining 13.1% is another variable not examined in this study. This means the model is getting stronger in explaining the effect of the independent variables studied on the dependent variable.

Statistical Data Testing

Used to test whether each independent variable has a positive or significant effect on the dependent variable. The statistical t-test value will be compared with the t-table value with an error rate of α = 5%. The t-table value with a significance level of 95% is 1.96. The limit for rejecting and accepting the proposed hypothesis refers to the value of 1.96. A hypothesis will be accepted if it has a t-statistic greater than 1.96 a otherwise smaller than 1.96, the hypothesis will be rejected.

Table 7. Path Coeficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
X1 -> Y1	0,002	0,013	0,073	0,025	0,980
X2 -> Y1	0,076	0,076	0,052	1,446	0,149
X3 -> Y1	0,473	0,472	0,095	4,953	0,000
X4 -> Y1	0,409	0,401	0,107	3,838	0,000

The table above shows that in this study, the t-statistic value for variable X1 (perceived usefulness) is 0.025 and the p-value of 0.980. This indicates that perceived convenience does not affect technology-based AIK learning because the t-statistic value is 0.025 < 1.96 and p-values 0.980> 0.05. The t-statistic value for variable X2 (Ease of Use) is 1.466, and the p-value of 0.149. This indicates that ease of use does not affect technology-based AIK learning because the t-statistic value is 1.466> 1.96 and the p-value is 0.0149> 0.05.

The t-statistic value for variable X3 (Attitude) is 4.953, and the p-value of 0.000. This indicates that attitude affects technology-based AIK learning because the t-statistic value is 4.953> 1.96 and the p-value is 0.000 <0.05. The t-statistic value for variable X4 (Behavioral Intention) is 3.838 and p-values of 0.000, which shows that Behavioral Intention affects technology-based AIK learning because the t-statistic value is 3.838> 1.96 and p-values 0.000 <0.05.

Discussion

This research provides valuable and comprehensive insights into the factors influencing the adoption, acceptance, and overall effectiveness of technology-based AIK learning. The statistical analysis conducted in this study reveals that the perceived usefulness (X1) variable does not significantly impact AIK learning in a technology-based environment. This conclusion is drawn based on the t-statistic value of 0.025, well below the critical threshold of 1.96, and a p-value of 0.980, considerably greater than the conventional significance level of 0.05. These results suggest that students may not necessarily perceive technology-based AIK learning as inherently beneficial, or that the role of perceived usefulness may be overshadowed by other, more influential factors in this specific learning context. Students may also require additional guidance or exposure to fully recognize the advantages of integrating technology into AIK learning processes. This is in line with research conducted by. There must be guidance in using digital learning. Students must be well-directed and given instructions on the operation of digital learning so that students can understand the benefits and convenience of the digital learning system.

Similarly, the ease of use (X2) variable does not demonstrate a statistically significant impact on technology-based AIK learning. This finding is supported by a t-statistic value of 1.466 and a p-value of 0.149, both of which indicate that the effect of ease of use on AIK learning engagement is not substantial. While ease of use is often considered a crucial element in the successful adoption of technology, in this particular scenario, it may not serve as the primary determining factor in students' engagement with learning (Dontre, 2021). Instead, students may place higher importance on aspects such as personal motivation, content relevance, interactive learning experiences, or their pre-existing familiarity with digital learning tools; This is in line with the results of research conducted by (Pereira, 2019)(Richard, 2019)Ease is not the main factor for students to open the learning system, but good content will be seen more often by students, because it is considered fun and not boring. This implies that even if the technology is user-friendly, other underlying elements must be addressed to enhance engagement levels effectively.

On the other hand, attitude (X3) emerges as a significant determinant in technology-based AIK learning, as indicated by a t-statistic value of 4.953 and a p-value of 0.000. This highlights that students' attitudes toward AIK learning influence their acceptance and willingness to engage with technology-enhanced learning methods actively. A positive attitude towards digital learning solutions will likely result in higher participation rates and a more immersive learning experience (Stachl, 2020)(Dontre, 2021). This finding underscores the need for educational institutions to cultivate and reinforce positive perceptions of technology-based learning, as students with favorable attitudes are more inclined to explore and embrace these modern educational tools.

Furthermore, behavioral intention (X4) is another key factor significantly influencing technology-based AIK learning. The statistical results, which present a t-statistic value of 3.838 and a p-value of 0.000, confirm that students' intentions to utilize technology in AIK learning substantially determine its actual adoption and effectiveness. A strong behavioral intention implies that when students are positively inclined and encouraged to integrate technology into their learning processes, they are more likely to engage with digital resources actively, ultimately enhancing their overall educational experience; This suggests universities and educators should implement strategies to reinforce students' willingness to adopt technology by highlighting its long-term benefits and providing necessary support structures to facilitate seamless integration.

The results in this study are by the hypothesis offered, it's just that the convenience variable does not affect the digital learning system, this is because the content created by the teachers is less interesting for the students, If the learning material is not interesting or relevant, students may not be involved even though the application is easy to use. This is the research finding, so teachers must make learning content as interesting as possible, so that students can be directly involved in digital learning.

4. CONCLUSION

The conclusion are this study the t-statistic value for variable X1 (perceived usefulness) is 0.025 and p-values of 0.980, which indicates that perceived convenience does not affect technology-based AIK learning because the t-statistic value is 0.025 < 1.96 and p-values 0.980> 0.05. The t-statistic value for variable X2 (Ease of Use) is 1.466 and p-values of 0.149; This indicates that ease of use does not affect technology-based AIK learning because the t-statistic value is 1.466> 1.96 and p-values 0.0149> 0.05. The t-statistic value for variable X3 (Attitude) is 4.953 and p-values of 0.000, which indicates that attitude affects technology-based AIK learning because the t-statistic value is 4.953> 1.96 and p-values 0.000 <0.05. The t-statistic value for variable X4 (Behavioral Intention) is 3.838 and p-values of 0.000, which shows that Behavioral Intention affects technology-based AIK learning because the t-statistic value is 3.838> 1.96 and p-values 0.000 <0.05. The Technology Acceptance Model (TAM) explains how users accept and adopt technology based on two main factors: perceived usefulness and perceived ease of use. In the context of AIK learning at Universitas Muhammadiyah Sumatera Utara (UMSU), TAM plays a crucial role in shaping the effectiveness and efficiency of technology-based learning.

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