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ENHANCING UTAUT FRAMEWORK TO EXPLAIN ACTUAL USAGE OF THE *SINAU* DIGITAL LEARNING MANAGEMENT SYSTEM WITH BEHAVIORAL INTENTION AS MEDIATING VARIABLE

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ABSTRACT

Phenomenon/Issue: The massive digital transformation in academia has integrated technology into teaching and learning. As an adaptive learning tool, LMS can optimize the management of academic information and learning activities. The students, in the faculty of economics and business, used LMS with various backgrounds and different levels of experience
Purpose: This study aims to examine usage behavior on the *Sinau* Digital Learning Management System educational platform through the application of the UTAUT model.
Novelty: This study was conducted in the context of technology acceptance in the academic field by developing UTAUT theory through role of Behavioral Intention.
Research Methods: This study used quantitative approach based on a survey of 344 students. The data were analyzed using Partial Least Square-Structural Equation Modeling (PLS-SEM).
Results: All hypotheses in this study were accepted. Each variable in the UTAUT model has a significant effect either directly or through the mediating variable of behavioral intention.
Research Contributions: The study expands the UTAUT framework by integrating Behavioral Intention as a mediator in LMS use, offering insights for optimizing system development in higher education.

INTRODUCTION

In recent decades, the growth of information and communication technology, particularly following the advances of the World Wide Web since the 1990s, has significantly influenced administrative and educational processes (Pacheco et al., 2025). The transformation of digital platfrom into academic community has occurred massively in recent years (Li et al., 2024). Many universities have adopted digital systems to enhance instructional effectiveness, strategic planning, and institutional performance. This transformation aligns with the Sustainable Development Goals (SDGs), which emphasize inclusive and high-quality education as a foundation for sustainable societal development (Ndibalema, 2025). However, despite its potential benefits, digital transformation in education still faces several challenges that may hinder effective implementation and digital inclusio (Kamali, 2024; Taam et al., 2024).

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E-learning develops a broader design and concept than online learning, called a Learning Management System (Rakhmawati et al., 2021). Universitas Negeri Surabaya has developed and implemented an LMS called *Sinau* Digital (Sindig) in its learning practices that integrates various e-learning platforms to facilitate students and lecturers in conducting digital-based lectures. Through the University's official website, UNESA achieved the 3rd best national predicate and won a bronze medal in the 2024 online learning ranking. Data on April 20, 2025, shows that the Faculty of Economics and Business, Universitas Negeri Surabaya, has the largest number of LMS users and courses. A total of 21,837 LMS users and 2,053 courses.

Once a system is accepted, the next step is ensuring continued use. The stronger the user's continuance intention, the more sustained the system's actual use (Rengganis & Nuryana, 2024). Unstructured interviews with six Faculty of Economics and Business students (Class of 2022) showed that digital learning is routinely used in academic activities when adequate internet access is available. This aligns with prior studies showing that students' perceptions of internet reliability and ease of use significantly influence their willingness to use it for academic purposes (Hasan & Khan, 2025). However, it remains unclear whether the use of *Sinau* Digital (Sindig) is consistently driven by intention, which ultimately determines actual usage. This uncertainty may create a gap between the system and student perceptions, leading to underutilization of available features. Therefore, intention plays a crucial role in integrating student perceptions and actual use of *Sinau* Digital.

The Unified Theory of Acceptance and Use of Technology (UTAUT) 1 contains four main constructs, namely Performance Expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating condition (FC) which tend to influence behavioral intentions to use a technology (Tariq et al., 2024). This theory has a significant role in the learning development process due to technological advances in the education sector (Rahma, 2023). UTAUT theory provides guidelines for research or exploration of technology acceptance used in the context of technology adoption in education (Ali et al., 2024).

Meiranto et al., (2024) examines the mediating role of behavioral intentions on factors influencing user behavior in the Indonesian Ministry of Finance's state financial application system using the UTAUT approach. This topic explains technology acceptance in the government sector, which is different from the *Sinau* Digital system in higher education. The differences are shown in the users, the purpose of the system, and the working environment.

Using UTAUT model to evaluate student usage intentions and behavior on the *Sinau* Digital (Sindig) LMS at Universitas Negeri Surabaya, this study provides fresh insights. According to the explanations, intention mediates actual usage. This study also has a theoretical objective to expand the application of the UTAUT model or construct in LMSs within higher education institutions, particularly at Universitas Negeri Surabaya.

LITERATURE REVIEW AND DEVELOPMENT HYPOTHESES

Information and communication technology

ICT has a tremendous impact on education, modifying how students learn and teach while also offering access to a wide range of educational materials such as online libraries, digital textbooks, educational websites, and multimedia content. This enables students to explore a wide range of topics, interact with learning resources, and learn autonomously. During the pandemic, ICT offered distance learning, which is the use of electronic technology to carry educational content (Shahzad et al., 2025).

Learning Management System (LMS)

An LMS can be defined as an information system that facilitates the creation, dissemination, and administration of learning content within the framework of Information Technology infrastructure development. Many types of LMS have become standard elements of Higher Education Institutions for the administration and delivery of online learning or learning management systems (Jiang et al., 2024). LMSs have grown into essential information and communication tools in higher education, formal, and non-formal education. Although LMS systems are the foundation of blended learning, they still have multiple disadvantages such as low or declining student motivation, engagement, focus, and interest, inefficient class activities, and feelings of isolation due to the loss of face-to-face interaction (Technol et al., 2025).

Unified Theory of Acceptance and Use of Technology (UTAUT)
An important role of a conceptual model is to explain IT adoption by identifying the factors that influence user intention and actual use (Venkatesh et al., 2003). The original version of UTAUT was developed from four main constructs: effort expectancy, social influence, and facilitating conditions, which tend to influence the intention to use a particular technology. Subsequent revisions were made to allow for application in organizational and consumer contexts by adding three new constructs: price value, habit, and hedonic motivation (Tariq et al., 2024). This study adopted the main constructs of UTAUT: Performance Expectancy and effort expectancy, which play a significant role in determining user behavioral intention and actual usage. Performance Expectancy is considered a measure of user confidence in using the system to help achieve work performance (Venkatesh et al., 2003). Effort expectancy examines how easy a technology is to use or perceived as a measure of the ease of use of a system using constructs from existing models: perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT) (Tariq et al., 2024).Behavioral intention is a measure of a person's subjective intention to perform an action or behavior. It is linked to the UTAUT model, which focuses on user intention in using a system by identifying four driving constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Alblooshi & Abdul Hamid, 2022).Users decide to use a system or technology by integrating knowledge and experience. Measures the extent to which users utilize technology to achieve goals (Muhamad et al., 2025). Actual usage refers to users' decisions to use a system or technology based on their knowledge and experience, reflecting how extensively it is used to achieve specific goals (Muhamad et al., 2025).

DEVELOPMENT HYPOTHESIS

Performance Expectancy refers to an individual's belief that using a system will enhance performance. Goals and needs at the time intentions are formed strongly influence technology use. Although usage intentions may change over time, actual behavior reflects the realization of these intentions (Alblooshi & Abdul Hamid, 2022). Performance expectations can improve students' learning experiences and outcomes. Another impact is that educators and administrative staff realize that using an LMS can save time, increase efficiency, and reduce administrative burdens, making them more likely to adopt it (Shahzad et al., 2025). In the research Chen et al., (2024) found that performance expectations contribute to usage intentions. Based on this description, the following hypothesis can be formulated:
H1: Performance Expectancy (PE) has a significant and positive influence or contribution to Actual Usage (AU).
H2: Performance Expectancy (PE) has a significant and positive influence or contribution to Behavioral Intention (AU)

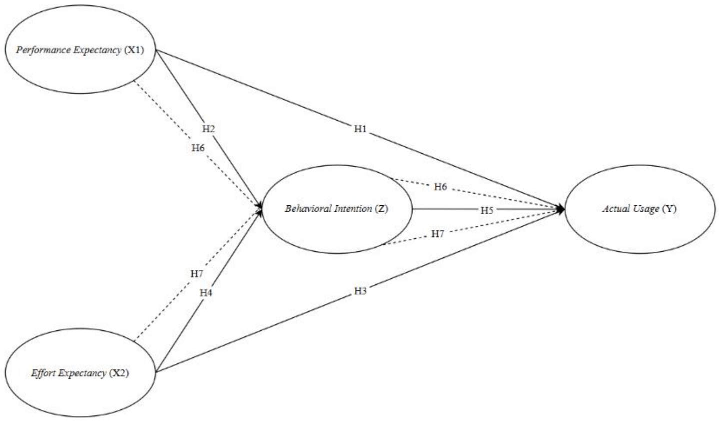
Effort Expectancy refers to an individual's perception of ease and comfort in using a system. This study examines students' comfort and convenience in using *Sinau* Digital to support academic activities. Effort expectancy is an intrinsic aspect of system acceptance that helps determine the level of commitment to using the system. Willingness to use the system is directly influenced by effort expectancy (Muhamad et al., 2025). In the research Suliman et al., (2024) shows the influence of business expectations on usage intentions.
H3: Effort Expectancy (EE) has a significant and positive influence or contribution to Actual Usage (AU)
H4: Effort Expectancy (EE) has a significant and positive influence or contribution to Behavioral Intention (BI).

Behavioral intention is a person's willingness and effort to engage in a behavior. When someone intends to use a product, they will intend to continue the behavior. In research (Meiranto et al., 2024) found that behavioral intention has a mediating role in usage behavior. Study by (Tariq et al., 2024) and (Ramadhina et al., 2025) behavioral intention mediates the main construct on usage.

H5: Behavioral Intention (BI) has a significant and positive influence or contribution to Actual Usage (AU)

H6: Behavioral Intention (BI) mediates between Performance Expectancy (PE) and Actual Usage (AU)

H7: Behavioral Intention (BI) mediates between Effort Expectancy (EE) and Actual Usage (AU)



Source: Processed Data (2025)

Figure 1 RESEARCH DESIGN

METHOD

This study used a quantitative research approach with an explanatory design to examine the relationships among variables and explain technology usage behavior(Malhotra, 2020). The sampling technique used simple random sampling through the Slovin formula calculation from a number of students of the Faculty of Economics and Business who used the *Sinau* Digital, LMS developed by UNESA. Then, a total of 344 students were obtained as research respondents who participated in filling out the questionnaire via Google form. The statement instrument used the Likert scale measurement method and was obtained from previous research that had been adjusted to the research needs. The statement items have been tested for validity and reliability on a number of 34 UNESA students who are not from Faculty of Economics and Business. Data analysis was conducted using Partial Least Squares–Structural Equation Modeling (PLS-SEM) to assess the measurement and structural models.

RESULTS AND DISCUSSIONS

This study included active students from the Faculty of Economics and Business, class of 2021 and 2022, who were assessed to have used the LMS for the longest period of time at the time the research was conducted.

Table 1 DISTRIBUTION OF RESEARCH RESPONDENTS' STUDY PROGRAM DATA

Study program	Amount	Percentage
Bachelor of Accounting	32	9%
Bachelor of Digital Business	34	10%
Bachelor of Economics	28	8%
Bachelor of Islamic Economics	40	12%
Bachelor of Management	32	9%
Bachelor Office Administration Education	70	20%
Bachelor of Accounting Education	29	8%
Bachelor of Business Education	48	14%
Bachelor of Economics Education	31	9%
Total	**344**	**100%**

Source: Processed data (2025)

Table 1 shows that the research respondents consist of students in each undergraduate study program at the Faculty of Economics and Business. The largest number of participants came from the Office Administration Education study program, representing 20% of all research respondents. Meanwhile, the fewest participants came from the Economics and Accounting Education study programs, representing 8% each.

Table 2 GENDER, CLASS, AND INTENSITY OF USE OF RESEARCH RESPONDENTS

Information		Amount	Percentage
Gender	Man	79	23%
	Woman	265	77%
	Total	**344**	**100%**
Class	2021	35	10%
	2022	309	90%
	Total	**344**	**100%**
Intensity of use	Every day	49	14%
	5-6 times a week	47	14%
	4-5 times a week	89	26%
	2-3 times a week	104	30%
	Once a week	55	16%
	Total	**344**	**100%**

Source: Processed data (2025)

Table 2 shows that 265 female respondents and 79 male respondents from the classes of 2021 and 2022, respectively. The table shows a percentage of 10% for the class of 2021. This is because at the time of data collection, many students from the class of 2021 had already graduated and had already completed their degrees. Consequently, many were no longer engaged in mobility and activities on campus. The intensity of LMS use was at most 2-3 times a week, amounting to 30%.

Table 3 AVERAGE VALUE OF STATEMENT INSTRUMENT

Statement Instrument		Average value	Information
Performance Expectancy (X1)	X1.1	4.41	Strongly agree
	X1.2	3.99	Agree
	X1.3	4	Agree
	X1.4	4.13	Agree
	X1.5	3.65	Agree
Effort Expectancy (X2)	X2.1	4.29	Strongly agree
	X2.2	4.26	Strongly agree
	X2.3	4.17	Agree
	X2.4	3.64	Agree
	X2.5	3.92	Agree
	X2.6	4.15	Agree
Behavioral Intention (Z1)	Z1.1	4.10	Agree
	Z1.2	3.98	Agree
	Z1.3	3.74	Agree
	Z1.4	3.95	Agree
Actual Usage (Y1)	Y1.1	3.31	Neutral
	Y1.2	3.68	Agree
	Y1.3	3.78	Agree
	Y1.4	3.95	Agree

Source: Processed data (2025)

Based on the average results, table 3 shows that Performance expectancy has the highest mean value on the X1.1 instrument, and the lowest mean value on the X1.5 instrument. Furthermore, the variable Effort expectancy has the highest mean value on the X2.1 instrument, and the lowest mean value on the X2.4 instrument. Then the Behavioral intention has the highest mean value on the Z1.1 instrument, and the lowest mean value of 3.74 on the Z1.3 instrument. The variable Actual usage has the highest mean value on the Z1.4 instrument, and the lowest mean value on the Y1.1 instrument.

Outer Model Analysis

This test is carried out by analyzing the results of convergent validity, discriminant validity, and reliability tests.

Table 4 CONVERGENT VALIDITY OF CONSTRUCT AND FACTOR LOADING ITEMS

Construct		Loading	AVE	Note
Performance expectancy (X1)	X1.1	0.726	0.881	Valid
	X1.2	0.805		Valid
	X1.3	0.822		Valid
	X1.4	0.805		Valid
	X1.5	0.704		Valid
Effort expectancy (X2)	X2.1	0.714	0.581	Valid
	X2.2	0.802		Valid
	X2.3	0.761		Valid
	X2.4	0.725		Valid
	X2.5	0.752		Valid
	X2.6	0.813		Valid
Behavioral intention (Z)	Z1.1	0.857	0.719	Valid
	Z1.2	0.872		Valid
	Z1.3	0.838		Valid
	Z1.4	0.825		Valid
Actual usage (Y)	Y1.1	0.799	0.663	Valid
	Y1.2	0.859		Valid
	Y1.3	0.853		Valid
	Y1.4	0.739		Valid

Source: Processed data (2025)

Table 4 shows the results of convergent validity testing for the reflective constructs. Convergent validity was evaluated using the outer model and Average Variance Extracted (AVE) (Hair et al., 2017). Tested using outer loading values with criteria > 0.70 and using Average Variance Extracted (AVE) with criteria of values equal to 0.50 or more (AVE> 0.50). The test results in table 4 state that each indicator in the variables Performance Expectancy, effort expectancy, behavioral intention, and actual usage has a loading factor value > 0.70. So all statement items can be said to be valid. Likewise, a variable can be said to be valid if it has an AVE value > 0.50. Therefore, each research variable shows an AVE value > 0.50. So the variable are valid.

Table 5 CONSTRUCT RELIABILITY

Variables	Cronbach's Alpha	CR	Note:
PE (X1)	0.831	0.881	Reliable
EE (X2)	0.855	0.892	Reliable
BI (Z)	0.870	0.911	Reliable

Variables	Cronbach's Alpha	CR	Note:
AU (Y)	0.829	0.887	Reliable

Source: Processed data (2025)

Table 5 shows that the reliability test in this exploratory study used an analysis method through Cronbach's Alpha with a value of > 0.60 and Composite Reliability with a value of > 0.70. The results of the analysis are in Table 5 which shows that each Cronbach Alpha and Composite Reliability value of each variable is more than 0.60 and 0.70, respectively, so each variable can be said to be reliable.

Table 6 VALIDITY OF DISCRIMINANT HTMT RATIO

Variables	HTML
Performance Expectancy (X1) <-> Actual Usage (Y)	0.790
Performance Expectancy (X1) <-> Behavioral Intention (Z)	0.872
Effort Expectancy (X2) <-> Actual Usage (Y)	0.752
Effort Expectancy (X2) <-> Behavioral Intention (Z)	0.808
Behavioral Intention (Z) <-> Actual Usage (Y)	0.776
Performance Expectancy (X1) <-> Effort Expectancy (X2)	0.846

Source: Processed data (2025)

Table 6 shows the results of the discriminant validity assessment using the Heterotrait–Monotrait Ratio (HTMT). HTMT measures the average correlation between indicators from different constructs (heterotrait–heteromethod) and compares it with the geometric mean of correlations between indicators within the same construct (monotrait–heteromethod) (Hair et al., 2017). Practically, the actual correlation estimate through the HTMT approach between two constructs with the provision of a value <0.90. The results of the discriminant validity test in Table 6 for the two constructs through the HTMT test show a value <0.90. Therefore, it can be concluded that it is valid or fulfilled.

Inner Mode Analysis

This stage involves several tests, namely the R-Square, Q-Square, effect size and Collinearity tests.

Table 7 R-SQUARE

Variables	R-square (R^2)
Behavioral Intention (Z)	0.529
Actual Usage (Y)	0.611

Source: Processed data (2025)

R-square is used to analyze how much an endogenous latent variable influences other latent variables. The criteria for this test are: if the R^2 value is 0.75, categorized as substantial (large/strong), if the R^2 value is 0.50, categorized as moderate, and if the R^2 value is 0.25, categorized as weak (small) (Hair et al., 2017). Table 7 shows that the magnitude of the influence of the Performance Expectancy and Effort Expectancy variables on the Behavioral Intention variable is 0.529, which is 52.9% of the influence is categorized as moderate. The remaining 47.1% is explained by other factors outside the research model such as environmental influences, university policies in the use of LMS, and others. Meanwhile, the magnitude of the influence of the Performance Expectancy and Effort Expectancy variables through Behavioral Intention on Actual Usage is 0.611 or 61.1%, meaning that it has a substantial or large impact. Therefore, the R-Square value for both variables is included in the moderate to strong category, which can be assumed that the research model has a fairly good explanatory ability in describing the relationship between variables contained in the topic of using *Sinau* digital by Students.

Table 8 Q-SQUARE

Variables	Q-square (Q^2)
Behavioral Intention (Z)	0.431
Actual Usage (Y)	0.336

Source: Processed data (2025)

The test is used to determine the model's predictive ability to measure the data. The criteria used are: if the Q^2 value is > 0, then the model has good predictive relevance. Meanwhile, if the Q^2 value is < 0, then the model does not have good predictive relevance. Table 8 shows the results of the Q^2 test using the blindfolding method. Based on the test results, the Q^2 values for the Behavioral Intention and Actual Usage variables have values > 0. Thus, the research model not only has a strong relationship between variables (based on the R^2 value), but also has good empirical predictive power (based on Q^2).

Table 9 EFFECT SIZE

	PE(X1)	EE(X2)	BI(Z)	AU(Y)
PE(X1)			0.305	0.054
EE(X2)			0.147	0.054
BI(Z)				0.073
AU(Y)				

Source: Processed data (2025)

The effect size test is conducted to determine the level of contribution of an independent variable to the dependent variable. It has three categories of values: 0.02, 0.15, and 0.35, each representing a small, medium, and large effect of the exogenous latent variable. An effect size value of less than 0.02 indicates no influence or effect (Hair et al., 2017). Table 9 shows that the Performance Expectancy variable has a moderate to large influence or impact on the Behavioral Intention variable ($f^2 = 0.305$), indicating that the perceived benefits of using an LMS contribute strongly to shaping students' intention to use the system. Furthermore, the influence on Actual Usage (Y) generally has a small f^2 value. Actual Usage is more strongly influenced by intention (Z) than directly by the expectation factor, namely variables X1 and X1.

Table 10 INNER MODEL COLLINEARITY

	PE(X1)	EE(X2)	BI(Z)	AU(Y)
PE (X1)			2,074	2,707
EE (X2)			2,074	2,378
BI (Z)				2,569
AU (Y)				

Source: Processed data (2025)

Table 11 OUTER MODEL COLLINEARITY

Statement Instrument		VIF
Performance expectancy (X1)	X1.1	1,537
	X1.2	1,952
	X1.3	2,024
	X1.4	1,806
	X1.5	1,483
Effort expectancy (X2)	X2.1	1,756
	X2.2	2,268
	X2.3	1,901
	X2.4	1,701
	X2.5	1,877
	X2.6	2,095
Behavioral intention (Z)	Z1.1	2,355
	Z1.2	2,535
	Z1.3	1,986
	Z1.4	1,970
Actual usage (Y1)	Y1.1	2,114
	Y1.2	2,349
	Y1.3	2,018
	Y1.4	1,440

Source: Processed data (2025)

Collinearity testing is performed to evaluate the inner model to ensure there is no multicollinearity between latent variables, or in other words, there is no overlap between independent variables in explaining other variables. The tolerance value (VIF) for each predictor construct must be greater than 0.20 (less than 5) (Hair et al., 2017). Through the results of the structural model collinearity (VIF) test in table 10, all VIF values are in the range of 2.074 to 2.707, or below the maximum limit of 5. Next is the Collinearity (VIF) test for the outer model in table 11, namely the test between indicators against their respective constructs (X1, X2, Z1, Y1). Based on tables 10 and 11, the results of the collinearity test on the inner and outer models show that all statement item indicators and constructs have values below the maximum limit of 5.0, therefore it can be concluded that there is no multicollinearity problem between indicators and constructs.

Hypothesis Testing

Table 12 PATH COEFFICIENT AND SIGNIFICANCE

	Original Sample (O)	T-Statistics	p-Value	Note
X1-Y	0.262	3,099	0.002	Accepted
X1-Z	0.496	7,981	0.000	Accepted
X2-Y	0.247	3,429	0.001	Accepted
X2-Z	0.433	5,227	0.000	Accepted
ZY	0.297	4,212	0.000	Accepted

Source: Processed data (2025)

Testing was conducted using the bootstrapping method. T-statistics and p-values were obtained with a p-value <0.05 criterion to assume a significant effect. If the Original Sample (O) value is positive, the relationship between the variables has a positive effect. Vice versa. Table 12 shows that the p-value is <0.05 and the path coefficient is positive. Therefore, H1, H2, H3, H4, and H5 are accepted as having a significant and positive effect.

Table 13 MEDIATION TEST

	***Original Sample* (O)**	**T-Statistics**	**p-Value**	**Note:**
X1-Z-Y	0.102	3,770	0.000	Accepted
X2-Z-Y	0.147	3,050	0.002	Accepted

Source: Processed data (2025)

The hypothesis testing results show p-values below 0.05, ranging from 0.000 to 0.002. As presented in Table 13, the path coefficients are positive, and T-Statistics value that meets the criteria $t > 1.96$ for $\alpha = 0.05$. In addition, all p-values meet the criteria <0.05. Therefore, hypotheses H6 and H7 are accepted, indicating that Performance Expectancy (X1) and Effort Expectancy (X2) have a significant positive effect on Actual Usage (Y) through the mediating role of Behavioral Intention (Z).

The Influence of Performance Expectancy on Actual Usage.

Performance expectancy was found to have a positive and significant effect on actual usage of the system, indicating that students who perceive the LMS as beneficial for enhancing their academic performance are more likely to use it consistently. This finding is consistent with previous studies by Razi-ur-Rahim et al. (2024) and Maisha & Shetu (2023). In the context of this study, students perceived that the existence of an LMS could assist academic activities. This perceived benefit encouraged students not only to have the intention to use but also to actually use the system. These results confirm that perceived performance benefits play a crucial role in transforming intention into actual usage, reinforcing the UTAUT framework that identifies performance expectancy as a primary driver of technology adoption and sustained use.

The Influence of Performance Expectancy on Behavioral Intention.

Performance expectancy was found to have a positive and significant effect on behavioral intention, indicating that stronger beliefs regarding a system's performance benefits increase users' intention to adopt and continue using the system. This finding is consistent with previous studies conducted by Chen et al. (2024), Muhamad et al. (2025), van Bussel et al. (2022), Sulimat et al. (2024) and Ali et al. (2024). Based on the results and findings of previous studies, it can be concluded that belief in the benefits of system performance plays an important role in shaping users' intention to use the system continuously. In this study, students perceived that the LMS was beneficial in academic life, thus encouraging the intention to use the LMS. In line with the UTAUT concept, perceived usefulness is an important factor in shaping behavioral intention.

The Influence of Effort Expectancy on Actual Usage.

Effort expectancy was found to have a positive and significant effect on actual usage, indicating that students who perceive the system as easy to use are more likely to engage with it regularly. This finding suggests that ease of use reduces barriers to interaction and encourages sustained system utilization. The result is consistent with the findings of Nwibe & Ogbuanya (2025). which highlight effort expectancy as an important determinant of actual technology use. Based on these results and the findings of previous research, it can be concluded that belief in the ease of use of a system plays a significant role in shaping user behavior towards actual use of the system. The easier an LMS is to understand and use, the higher the level of actual use by students. This is in line with the UTAUT model that Effort expectancy is a significant factor driving the actual use of a system.

The Influence of Effort Expectancy on Behavioral Intention.
Effort expectancy was found to have a positive and significant effect on behavioral intention. The higher the belief in the ease of use of the system, including the ease of understanding and operation of the system, the more it will encourage user intention to use. This is in accordance with research by Al-Adwan et al. (2024) and Suliman et al. (2024). In the context of this study, the ease of operation of the LMS encourages students to have the intention to use it. This is in line with the UTAUT concept that effort expectancy is an important factor in shaping behavioral intention.

The Influence of Behavioral Intention on Actual Usage.
Behavioral intention was found to have a positive and significant effect on actual usage. The motivation to use the LMS Sinau digital directly influences actual usage by students of the Faculty of Economics and Business, UNESA. This is in accordance with research conducted by Ali et al. (2024), Maisha & Shetu (2023), Alblooshi & Abdul Hamid (2022), and Razi-ur-Rahim et al. (2024). In the context of this study, the actual LMS usage factor is influenced by the motivation to use. This is in line with the UTAUT model, which states that behavioral intention is a predictor of actual usage.

The Influence of Performance Expectancy on Actual Usage through Behavioral Intention as a Mediating Variable
Performance expectancy was found to have a positive and significant effect on actual usage through behavioral intention as a mediating variable. When achieving actual use of the UNESA digital learning LMS, not only is the performance expectation indicator fulfilled or achieved, but there is also a drive for intention within the student so that the actual system is used in the academic process. In accordance with research by Alblooshi & Abdul Hamid (2022), Tariq et al. (2024), Nwibe & Ogbuanya (2025), this finding strengthens the UTAUT theory which places behavioral intention as a mediator between performance expectations and actual technology use.

The Influence of Effort Expectancy on Actual Usage through Behavioral Intention as a Mediating Variable
Effort expectancy was found to have a positive and significant effect on actual usage through behavioral intention mediation. Perceived ease of use of the Sinau Digital LMS drives students' intention to use it, which is then manifested in actual usage behavior. This is in accordance with research conducted by Nwibe & Ogbuanya (2025). Overall, the results of this study indicate that students' belief in the ease of use of the Sinau Digital LMS as an academic system will encourage the formation of intention to use it. This will then have an impact on increasing actual usage.

CONCLUSION

This study provides empirical evidence supporting the use of the UTAUT model in explaining students' actual usage of *Sinau* Digital Learning Management System. The results show that all proposed hypotheses were supported, showing that performance expectancy and effort expectancy significantly influence actual usage, both directly and indirectly through behavioral intention. Overall, this study confirms that trust in the benefits of the Sinau digital LMS and perceived ease of use play an important role in encouraging students to use Sinau Digital. Behavioral intention is proven to act as a mediator connecting student perceptions with actual use in the field, thereby increasing the effectiveness of the Sinau digital LMS use in supporting the learning process at the Faculty of Economics and Business, UNESA. This study has several limitations that are important to consider in the process of interpreting the results and generalizing the findings. The first limitation is that this study was only conducted within the scope of students of the Faculty of Economics and Business, UNESA, consisting of study programs in Economics Education, Business Education, Accounting, Accounting Education, Management, Digital Business, Business Education, Economics, Office Administration Education, and Islamic Economics with the criteria of Sinau digital LMS users of the 2021-2022 intake. This means that the results of the study cannot be generalized to all UNESA students. Furthermore, it is limited to the UTAUT construct. Therefore, in further research, it can be considered to research all students of

Universitas Negeri Surabaya and can use mixed research methods, namely combining quantitative and qualitative and utilizing the UTAUT model as a whole in order to dig deeper into the experience of using a system.

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