Exploring the Factors Affecting the Student's Acceptance of Using IAIN Ponorogo E-Learning through the UTAUT Model

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Abstract

This study aims to analyze the factors affecting the student's acceptance of e-learning IAIN Ponorogo through the UTAUT model, which consists of four primary constructs: performance expectancy, effort expectancy, social influences, and facilitating conditions. Those constructs are influenced strongly by moderating variables, which include age, gender, experience, and volunteerism of use. This model will be used to analyze the e-learning system of IAIN Ponorogo based on LMS Moodle version 1.9.15 with slight modifications. The research type is quantitative-explanative research. The subjects are students of IAIN Ponorogo, with 400 respondents as a sample from a total population of 8112 students using a stratified random sampling technique. Data was collected from the results of a closed questionnaire and analyzed by the Partial Least Square (PLS) method with WarpPLS software, which consists of three steps: the design of the inner model, the outer model, and the evaluation of the model. The findings indicated that: (1) Facilitating condition factors have a positive and insignificant effect on students' behavior with a parameter coefficient value of 0.7% and a p-value greater than 5%; (2) The interest in use factor has a positive and significant effect on the use behavior of students with a parameter coefficient value of 0.735 and a p-value greater than 5%.

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INTRODUCTION

There is a phenomenon of the COVID-19 pandemic, which started in the city of Wuhan, China, at the end of 2019 and quickly spread almost throughout the world until now. [1] [2] [3] The circumstances require all lines to adapt to changes in life patterns, including education. In a short time, educational institutions are forced to implement online or distance learning to face it, where information and communication technology play an essential role. [4] [5] [6] It is estimated that around 97% of educational institutions have implemented online learning. [7]

In response to the COVID-19 pandemic and the increasingly rapid development of information technology, a digital service must be used as an effective distance learning medium for students. One use of information technology that educational institutions commonly use is E-learning. E-learning is a media that is currently popular and is being massively developed by various educational institutions. [8] [9] [10] [11] The application of E-learning has at least four benefits: personal experience in learning, reduced costs, ease of achievement, and the ability to be responsible. [12]

IAIN Ponorogo's digital learning system, which has a page https://e-learning.iainponorogo.ac.id, allows it to be updated regularly, and the latest currently is version 3.6.1. Some of the Moodle features that have been implemented in IAIN Ponorogo E-learning are course categories (material categories based on faculties and study programs), online users, online tests, messages, calendar, discussion, IAIN Ponorogo's site, news, and so on. This interactive and systematic E-learning display is straightforward to use; the material can also be downloaded so that everyone can study it in offline method. With E-learning, interaction between students and lecturers will be easier and more interactive because it can be done anywhere and anytime without being bound by distance and time. Ideally, all lecturers and students can optimally utilize this kind of convenience for the smoothness and effectiveness of distance learning. Previous studies show that the effectiveness of e-learning in some Indonesian Islamic Universities is at a score of 52% in the outstanding category and is reflected in student responses. Learning can make students active, independent, think critically, responsible, collaborate, and discuss according to learning objectives [13] [14] and a statistically significant increase in mean summative assessment score ($P = 0.03$) and final grade ($P = 0.02$) for students who completed the formative e-learning module. [15]

According to researchers' observations, the level of use and acceptance of IAIN Ponorogo E-learning is less than optimal and still faces many obstacles. This is reflected in the unequal distribution of lecturers who use IAIN Ponorogo E-learning in the learning process, with a percentage of 60%, and the level of knowledge and mastery of students being inadequate. The use of e-learning is also limited to technical issues, including network access and e-learning platforms. It has yet to enter into more substantive issues and productive learning interactions. [16] Furthermore, there are still students who need to learn about using E-learning in the campus environment, so in practice, many lecturers and students do not use this platform. However, on the other hand, the massive use of the E-learning platform will increase the campus ranking on Webometrics, where in mid-July 2021, the IAIN Ponorogo campus was ranked 18th out of 58 Islamic State University's in Indonesia and 160th out of 2593 Islamic State University's in Indonesia.[17] Furthermore, several aspects need improvement, namely internet quota, quality of learning media, and learning facilities.[18]

On the one side, the use of information technology provides many benefits, but on the other side, it may also not bring benefits due to the inability of institutions that fail to plan and implement information technology. Many projects developing an online learning system still need to produce a system that provides benefits. [19, pp. 23–24] Many factors, both internal and external, can cause failure to implement information technology systems in this institution. Among them is the need for more synchronization between the decisions made and the level of user acceptance. The decision to adopt an information technology system is in the hands of policymakers. However, the successful use of this technology in the field depends on the acceptance and use of all individual users. System user behavior is formed from the user's attitudes and perceptions of the system. Information technology users are humans who psychologically have a specific behavior inherent to them, so behavioral aspects in the context of humans as users of information technology are essential as a determining factor in the success of implementing information technology.

Therefore, it is essential to know the level of acceptance and user perceptions of IAIN Ponorogo E-learning. One way to measure the level of user perception is within the UTAUT model or Unified Theory Of Acceptance And Use Of Technology. This model includes a model for measuring technology acceptance developed by Venkatesh et al., where this model is a combination of the eight leading acceptance theories, namely TRA, TAM, MM, TPB, combining TAM and TPB, MPTU, IDT, and SCT. Venkatesh et al. found four primary constructs that play an essential role as direct determinants of behavioral intention and use behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. [20, pp. 425–478]. Many similar studies have been carried out, especially regarding UTAUT, to measure the acceptance and use of a particular technological system. [21] [22] [23].

Previous studies on the technology acceptance on online learning platforms in Universities have mainly focused on the impact of cognitive absorption [24], the behavioral differences in the acceptance [25], and the role of student competency [26] in integrating the technology acceptance model and S-O-R model [27]. An increasing number of scholars have examined emerging technologies and the use of devices with various acceptance models, yet research has scarcely explored users' intentions to accept innovative online learning media relevant to the sense of trust. Meanwhile, trust is considered an important factor that promotes the adoption of innovative technologies in various fields [28] and trust in online learning media enables the users to have confidence in the device's performance, safety, and effectiveness.[29] The unique aspect of this study is that it will fully implement Venkatesh's UTAUT model, which includes independent, dependent, and moderator variables, to determine whether strengthening the relationship between the two variables mentioned above is necessary. The study will also examine the system's use from the viewpoint of student users and the urgency of doing so, given the Covid-19 pandemic's demand for online learning. This study examines the variables influencing the adoption and utilization of IAIN Ponorogo e-learning. This study adds to both theoretical understanding and real-world applications in the rapidly changing field of learning technology by concentrating on the distinctive features of cutting-edge online learning media. It also offers fresh insights into the process of technology acceptance among educators.

METHODS

This research uses explanatory research, which explains the causal relationship between research variables through hypothesis testing. Analysis of acceptance and use in research uses the UTAUT model, designed to analyze what factors influence the acceptance and use of technology. The UTAUT model used is in Figure 1.

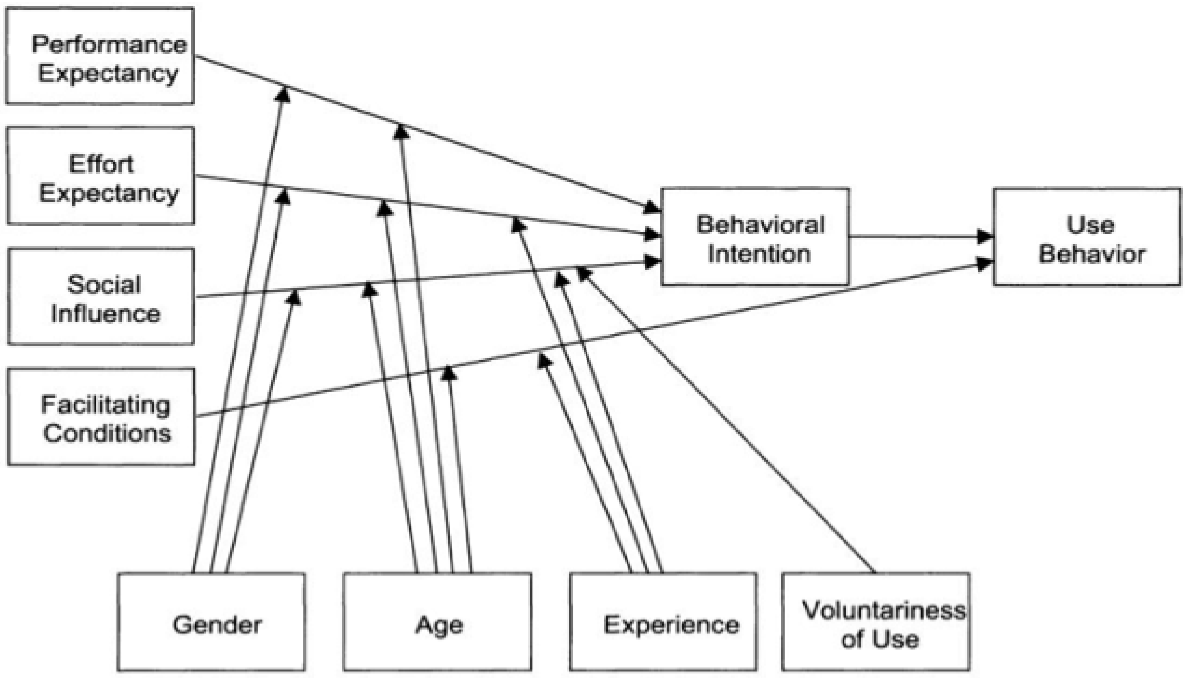

Figure 1. UTAUT Model as a Research Framework

The research sample was 400 IAIN Ponorogo students from a total population of 8112 students who used E-learning as of August 2021 with a sampling technique in the form of stratified random sampling. The data collection method uses a 5 Likert scale questionnaire, as the most widely used data collection method regarding the UTAUT model [30], with details: 1 strongly disagree, 2 disagree, 3 neutral, 4 agree, and 5 strongly agree.

Table 1. Likert Score

No.	Scale	Score
1.	Strongly Agree	5
2.	Agree	4
3.	Neutral	3
4.	Disagree	2
5.	Strongly Disagree	1

The instrument grid is structured based on indicators and constructs established in the UTAUT model, where this instrument consists of 42 statement items composed of four primary constructs, 3 secondary constructs, and 1 objective construct, and is equipped with seven sections. The first section contains several questions regarding respondents' characteristics, including name, gender, age, previous experience using E-learning, and willingness to use E-learning. The second part concerns performance expectations (9 statement items), the third section concerns business expectations (6 statement items), the fourth section relates to social factors (7 statement items), the fifth section concerns facilitating condition variables (11 statement items), then the sixth concerns usage interest (3 statement items) and the seventh section concerns usage behavior variables (2 statement items).

The data analysis technique used in this research is the PLS approach using WarpPLS software, which consists of the following 3 steps: 1) designing a structural model (inner model), 2) designing a measurement model (outer model), 3) measurement model which includes: outer model measurement, inner model measurement, and hypothesis testing.

RESULT AND DISCUSSION

This inferential analysis used for measurement is component-based SEM software, namely WarpPLS version 7.0. The choice of PLS was due to previous research closely related to utilizing this software. Additionally, WarpPLS is more user-friendly when used to test models with more than one moderate variable.

Outer model

The first thing the author did in evaluating the model measurements was to measure the outer model. Measuring the outer model is carried out in a variable to identify the reliability and validity of the indicator statement items. In this stage, the outer model measurement is carried out by looking at the convergent, discriminant, and composite validity values.

Convergent validity includes validity, proving that the scores obtained by two instruments that measure the same concept or concepts with different methods will have a high correlation. Convergent validity produces loading factor values for each construct. Loading factor values above 0.7 are highly recommended; however, loading factors of 0.50 to 0.60 can still be tolerated as long as the research model is still in development. For items that do not have a loading factor value above 0.5, the improvement process can be done by dropping or deleting the item. The following are the convergent validity results using WarpPLS.

Based on Table 2, we can understand that the convergent validity for each variable is as follows: (1) Convergent validity for the performance expectations variable is good because of the 9 statement items in the indicator; all have loading factor values above 0.5, and all are significant; (2) Convergent validity for the business expectations variable is good because of the 6 statement items in the indicator; all have loading factor values above 0.5, and all are significant; (3) Convergent validity for the social factor variable is good because of the 6 statement items in the indicator; all have loading factor values above 0.5, and all are significant; (4) Convergent validity for the facilitating condition variable is good because of the 10 statement items in the indicator, which all have loading factor values above 0.5 and are significant; (5) Convergent validity for the behavioral intention variable is good because of the 3 statement items in the indicator, which all have loading factor values above 0.5 and are significant; (6)

Convergent validity for the usage behavior variable is good because of the 2 statement items in the indicator; all have loading factor values above 0.5, and all are significant.

Table 2. Convergent Validity Results Without Moderate Variables

Indicator Items	x1	x2	x3	x4	z	y	P value
X1.1.1	0.861	0.040	-0.023	-0.099	-0.079	0.110	<0.001
X1.1.2	0.767	0.152	-0.049	-0.196	0.003	0.033	<0.001
X1.1.3	0.838	0.013	0.032	-0.141	0.101	-0.058	<0.001
X1.2.1	0.871	-0.087	-0.091	0.041	-0.050	0.040	<0.001
X1.2.2	0.685	-0.337	0.059	0.036	-0.242	0.101	<0.001
X1.3.1	0.840	0.024	-0.006	0.188	0.108	-0.129	<0.001
X1.3.2	0.830	0.207	0.059	-0.025	0.010	0.006	<0.001
X1.4.1	0.776	0.216	0.003	0.080	0.225	-0.097	<0.001
X1.4.2	0.734	-0.294	0.031	0.126	-0.114	0.005	<0.001
X2.1.1	0.008	0.844	-0.017	-0.252	0.010	-0.018	<0.001
X2.1.2	-0.166	0.796	-0.168	0.121	-0.181	0.099	<0.001
X2.1.3	-0.162	0.891	-0.099	0.075	-0.087	0.042	<0.001
X2.2.1	0.064	0.884	0.039	-0.039	0.176	-0.054	<0.001
X2.2.2	0.117	0.827	0.092	0.047	0.034	-0.006	<0.001
X2.2.3	0.139	0.842	0.150	0.054	0.036	-0.057	<0.001
X3.1.1	-0.249	0.022	0.626	-0.176	-0.159	0.110	<0.001
X3.1.2	0.066	-0.016	0.693	-0.104	-0.409	0.338	<0.001
X3.1.3	0.242	0.206	0.771	-0.011	0.141	-0.073	<0.001
X3.2.1	-0.060	-0.130	0.691	-0.164	-0.007	-0.019	<0.001
X3.2.2	-0.043	-0.044	0.798	0.006	0.204	-0.154	<0.001
X3.3.1	0.097	-0.003	0.817	0.267	-0.035	0.004	<0.001
X3.3.2	-0.098	-0.041	0.818	0.100	0.176	-0.140	<0.001
X4.1.1	-0.124	0.286	-0.117	0.811	-0.036	-0.001	<0.001
X4.1.2	0.020	0.179	-0.165	0.838	-0.041	-0.034	<0.001
X4.1.3	-0.305	0.481	-0.019	0.703	0.016	0.066	<0.001
X4.2.1	0.120	-0.160	-0.023	0.674	-0.123	-0.104	<0.001
X4.2.2	-0.162	-0.051	0.085	0.744	0.129	-0.049	<0.001
X4.2.3	0.186	-0.313	-0.033	0.757	-0.019	0.017	<0.001
X4.2.4	0.232	-0.291	-0.128	0.729	-0.194	0.069	<0.001
X4.3.1	0.207	-0.087	-0.109	0.750	-0.004	-0.031	<0.001
X4.3.2	-0.245	-0.210	0.519	0.357	0.002	0.187	<0.001
X4.3.3	-0.058	0.022	0.313	0.681	0.289	-0.025	<0.001
Z1.1	-0.002	-0.028	-0.104	0.090	0.934	-0.082	<0.001
Z1.2	-0.011	-0.037	-0.053	0.096	0.940	-0.007	<0.001
Z1.3	0.014	0.070	0.167	-0.197	0.883	0.094	<0.001
Y1.1	-0.099	-0.104	0.088	-0.036	-0.189	0.905	<0.001
Y1.2	0.099	0.104	-0.088	0.036	0.189	0.905	<0.001

Based on the resulting test in Table 2, all statement items have a loading factor value above 0.5, meaning all indicators have good convergent validity. The next check of convergent validity is by looking at the AVE output. Constructs have good convergent validity if the AVE value exceeds 0.50. The results of the AVE value are shown in Table 3. The AVE value of all research variables exceeds the value of 0.50. It means that performance expectations, effort expectations, social factors, facilitating conditions, interest in utilization, and usage behavior have good convergent validity values.

Table 3. AVE Value

Variable	AVE
Performance expectancy	0.644
Effort expectancy	0.719
Social influences	0.560
Facilitating conditions	0.512
Behavioral intention	0.845
Use Behavior	0.819

Discriminant validity includes the value of the cross-loading factor, which helps analyze whether some of these constructs have adequate discriminant, namely by comparing the loading value on the construct in question, which must be greater than the loading value with other constructs. Based on Table 3 above, we can understand that the results of discriminant validity for each variable are as follows:

Discriminant validity for the performance expectation variable is good because all indicator items each have a higher relationship value on the same variable when compared to the relationship value with other variables. In this variable, there are 9 statement items, where the item that has the lowest cross-loading factor value is item X1.2.2 of 0.685; this indicates that item X1.2.2 has the least discriminant or differentiating value when compared to other statement items on the independent variable performance expectations. Meanwhile, the item that has the highest cross-loading factor value is item X1.1.1, which is 0.861; this indicates that item X1.1.1 has the greatest discriminant or differentiating value if we compare it with other statement items on the independent variable performance expectations.

Discriminant validity for the business expectation variable is good because all indicator items have a higher relationship value on the same variable when compared to the relationship value with other variables. In this variable, there are 6 statement items, where the item that has the lowest cross-loading factor value is item X2.1.2 of 0.796; this indicates that item X2.1.2 has the least discriminant or differentiating value when compared to other statement items on the independent variable performance expectations. Meanwhile, the item that has the highest cross-loading factor value is item X2.1.3, which is equal to 0.891; this shows an indication that item X2.1.3 has the greatest discriminant or distinguishing value if we compare it with other statement items on the independent variable of business expectations.

Discriminant validity for social factor variables is good because all indicator items each have a higher relationship value on the same variable when compared to the relationship value with other variables. In this variable, there are 7 statement items, where the item that has the lowest cross-loading factor value is item X3.1.1 of 0.626; this indicates that item X3.1.1 has the least discriminant or differentiating value when compared to other statement items on the independent variable social factors. Meanwhile, the item with the highest cross-loading factor value is item X3.3.2, which is 0.818; this indicates that item X3.3.2 has the greatest discriminant or differentiating value if we compare it with other statement items on the independent variable social factors.

Discriminant validity for the facilitating conditions variable is good because all indicator items each have a higher relationship value on the same variable when compared to the relationship value with other variables. In this variable, there are 10 statement items, where the item that has the lowest cross-loading factor value is item X4.2.1 of 0.674; this indicates that item X4.2.1 has the least discriminant or differentiating value when compared to other statement items on the independent variable facilitating conditions. Meanwhile, the item with the highest cross-loading factor value is item X4.1.2, equal to 0.838; this indicates that item X4.1.2 has the greatest discriminant or differentiating value compared to other statement items on the independent variable of facilitating conditions.

Discriminant validity for behavioral intention variables is good because all indicator items each have a higher relationship value on the same variable when compared to the relationship value with other variables. In this variable, there are 3 statement items, where the item that has the lowest cross-loading factor value is item Z1.2 of 0.940; this indicates that item Z1.2 has the least discriminant or differentiating value if we compare it with other statement items on the independent variable behavioral intention. Meanwhile, the item with the highest cross-loading factor value is item Z1.3, which is 0.883; this indicates that item Z1.3 has the greatest discriminant or distinguishing value if we compare it with other statement items on the independent variable behavioral intention. Discriminant validity for the usage behavior variable is good because all indicator items each have a higher relationship value on the same variable when compared to the relationship value with other variables.

Table 4. Composite Reliability and Cronbach's alpha

Variable	*Composite reliability*	Cronbach's Alpha
Performance expectancy	0.942	0.930
Effort expectancy	0.939	0.921
Social influences	0.898	0.867
Facilitating conditions	0.911	0.889
Behavioral intention	0.942	0.908
Use Behavior	0.900	0.779

We utilize composite reliability to measure the reliability of latent variables. We generate Composite reliability from calculations using WarpPLS, where we want to say reliable if the composite reliability value is ≥ 0.70. Aside from the resulting composite reliability results, this measurement is also corroborated based on the value of Cronbach's alpha, which is said to be reliable if the Cronbach's alpha value is ≥ 0.60. Table 4 shows the results of composite reliability and Cronbach's alpha generated using WarpPLS:

Based on Table 4, we can understand that the results of composite reliability testing for each variable are categorized as good. This is because each variable has a composite reliability value above 0.7 and a Cronbach's alpha value above 0.6. In the results of measuring this composite reliability, we can understand that the variable with the lowest reliability value is the social factor variable, with a composite reliability value of 0.898 and a Cronbach's alpha value of 0.867. It can be concluded that the variable has the lowest reliability test value if we compare it with other variables. Meanwhile, the variables with the highest reliability value are the performance expectation and behavioral intention variables, namely the Composite reliability value of 0.942 and the Cronbach's alpha values of 0.930 and 0.908. It can be concluded that the variable has the highest reliability test value compared to other variables. From the results of measuring the outer model without utilizing the moderate variable above, the results of this measurement have met the validity and reliability of the model so that it can be continued to carry out inferential analysis utilizing moderate variables.

Inner model

After we have created the outer model, the next step is the inner model. At this stage, we need to pay attention to the parameter coefficient value, the T-Statistic value, and the significance of the parameter coefficient. We get the T-Statistic value from the bootstrapping results in WarpPLS. In measuring the inner model, we consider all variables necessary, whether they are independent, dependent, or moderate variables, and then want to use them as primary elements. The following are the results of measuring the inner model in this study.

Table 5. Hypothesis Test Model without Moderate Variable

Independent variable	Bound variable	Coefficient Value	p-value	Description
X1	Z	0.159	<0.001	Influential
X2	Z	0.394	<0.001	Influential
X3	Z	0.156	<0.001	Influential
X4	Y	0.077	0.058	Influential
Z	Y	0.735	<0.001	Influential

Based on Table 5, we understand that every variable relationship does not own positive coefficient values and significance values of less than 5%. Several variable relationships have positive coefficient values and significance values of less than 5%, as many as 4 relationships, indicating a positive relationship between the independent and dependent variables. [19]. The analysis is described as follows.

In the variable relationship, performance expectations and interest in use have a positive and significant relationship. This is because it has a positive coefficient value of 0.159 and a significance value of less than 5%. So, the performance expectation variable significantly affects the dependent variable of interest in use.

The variable relationship between business expectations and interest in use has a positive and significant relationship. This is because it has a positive coefficient value of 0.394 and a significance value of less than 5%. So, the business expectation variable significantly positively affects the dependent variable of interest in use.

In the relationship between social factor variables and interest in use, there is a positive and significant relationship. This is because it has a positive coefficient value of 0.156 and a significance value of less than 5%. So, the social factor variable significantly positively affects the dependent variable of interest in use.

In the relationship between facilitating conditions and usage behavior variables, there is a positive and insignificant relationship. This is because the positive coefficient value is 0.077 and has a significance value of more than 5%. So, the facilitating conditions variable has no significant positive effect on the dependent variable of usage behavior.

The variable relationship between interest in use and usage behavior has a positive and significant relationship. This is because it has a positive coefficient value of 0.735 and a significance value of less than 5%. So, the variable of interest.

Table 6. Hypothesis Test Model with Intervening Variables

Variable Relationship	Coefficient Value	p-value	Description
X1 – Z – Y	0.117	<0.001	Influential
X2 – Z – Y	0.290	<0.001	Influential
X3 – Z – Y	0.115	<0.001	Influential

Based on Table 6, we understand that work expectations, business expectations, and social factors have a positive and significant effect on usage behavior through an interest in use; this can be seen from the positive coefficient value and a significance value of less than 5%.

Table 7. Hypothesis Test Model with Moderate Variable

Independent variable	Bound variable	Coefficient Value	p-value	Description
x1	Z	0.205	<0.001	Influential
x2	Z	0.400	<0.001	Influential
x3	Z	0.180	<0.001	Influential
x4	Y	0.007	0.447	No Effect
z	Y	0.742	<0.001	Influential
Gx1	Z	0.034	0.246	No Effect
Gx2	Z	0.044	0.189	No Effect
Gx3	Z	0.008	0.433	No Effect
Ax1	Z	0.125	0.005	Influential
Ax2	Z	-0.046	0.177	No Effect
Ax3	Z	0.020	0.344	No Effect
Ax4	Y	0.044	0.189	No Effect
Ex2	Z	0.025	0.304	No Effect
Ex3	Z	0.021	0.333	No Effect
Ex4	Y	0.057	0.125	No Effect
Vx3	Z	0.041	0.205	No Effect
A	Z	0.014	0.387	No Effect
A	Y	0.067	0.088	No Effect
E	Z	0.073	0.069	No Effect
E	Y	-0.033	0.254	No Effect
G	Z	-0.036	0.232	No Effect

Based on Table 7, the results of hypothesis testing are obtained which can be described as follows: Hypothesis 1: Performance expectancy positively and significantly affects behavioral intention. The loading factor value of the performance expectation coefficient on interest in use is 0.205 or 20.5%, which means it is positive. The significance value of this path is less than 5%. This means that the performance expectation variable significantly positively affects interest in use [31]. Based on this, hypothesis 1 is accepted. Based on the previous descriptive statistical analysis, the indicator on the performance expectancy variable has a mean of 3.61 with 9 statement items. This shows that students who use IAIN Ponorogo e-learning strongly agree that the existence of individual confidence in using a technology system will increase their interest in using the system in their learning activities.

Hypothesis 1a: Gender strengthens the relationship between performance expectancy and behavioral intention. The loading factor value of the gender moderating variable on performance expectations on interest in use is 0.034 or 34%, which means it is positive. The significance value of this path is more than 5%. This means that the gender moderating variable on performance expectations does not significantly affect usage interest, so it cannot strengthen the relationship between the performance expectation variable and usage interest. Based on this, it can be concluded that hypothesis 1a is rejected.

Hypothesis 1b: Age strengthens the relationship between performance expectancy and behavioral intention. The loading factor value of the moderate age variable on performance expectations on interest in use is 0.125 or 12.5%, which means it is positive. The significance value of this path is less than 5%. This means that the moderate variable age on performance expectations significantly affects interest in the use so that it can strengthen the relationship between the performance expectation variable and interest in use. Based on this, hypothesis 1b is accepted.

Hypothesis 2: Effort expectancy positively and significantly affects behavioral intention. The loading factor value of the business expectation coefficient on interest in use is 0.400 or 40%, which means it is positive. The significance value of this path is less than 5%. This means that the business expectation variable significantly positively affects interest in use. [19]. Based on this, hypothesis 2 is accepted. Based on the previous descriptive statistical analysis, the indicator on the effort expectancy variable has a mean of 3.52 with 6 statement items. This shows that students who use IAIN Ponorogo e-learning strongly agree that the ease of using a technology system will arouse individual interest in using the system in their learning activities.

Hypothesis 2a: Gender strengthens the relationship between effort expectancy and behavioral intention. The loading factor value of the moderate variable gender on business expectations on interest in use is 0.044 or 0.4%, which means it is positive. The significance value of this path is more than 5%. It means that the gender moderating variable on business expectations does not significantly affect interest in use, so it cannot strengthen the relationship between the business expectation variable and interest in use. Based on this, it can be concluded that hypothesis 2a is rejected.

Hypothesis 2b: Age strengthens the relationship between effort expectancy and behavioral intention. The loading factor value of the moderate age variable on business expectations on interest in use is -0.046 or -0.4%, which means it is negative. The significance value of this path is more than 5%. It means that the moderate variable age in business expectations does not significantly affect interest in use, so it cannot strengthen the relationship between the business expectation variable and interest in use. Based on this, it can be concluded that hypothesis 2b is rejected.

Hypothesis 2c: Experience strengthens the relationship between effort expectancy and behavioral intention. The loading factor value of the moderate variable Experience on business expectations on interest in use is 0.025 or 0.2%, which is positive. The significance value of this path is more than 5%. This means that the moderate variable experience on business expectations does not significantly affect interest in the use, so it cannot strengthen the relationship between the business expectation variable and interest in use. Based on this, it can be concluded that hypothesis 2c is rejected.

Hypothesis 3: Social influence positively and significantly affects behavioral intention. The loading factor value of the social factor coefficient on interest in use is 0.180 or 18%, which means it is positive, and the significance value of this path is less than 5%. This means that the social factor variable significantly positively affects interest in using it. [19]. Based on this, hypothesis 3 is accepted. Based on the previous descriptive statistical analysis, the indicator on the social influence variable has a mean of 3.43 with 7 statement items. It shows that students who use IAIN Ponorogo e-learning strongly agree that the influence of people around them will arouse their interest in using technology systems in their learning activities.

Hypothesis 3a: Gender strengthens the relationship between social influence and behavioral intention. The loading factor value of the moderating variable gender on social factors on interest in use is 0.008 or 0.8%, which means it is positive. The significance value of this path is more than 5%. It means that the moderating variable gender on social factors does not significantly affect interest in use, so it cannot strengthen the relationship between social factors variables and interest in use. Based on this, it can be concluded that hypothesis 3a is rejected.

Hypothesis 3b: Age strengthens the relationship between social influence and behavioral intention. The loading factor value of the moderate age variable on social factors on interest in use is 0.020 or 0.2%, which means it is positive. The significance value of this path is more than 5%. It means that the moderate age variable in social factors does not significantly affect interest in use, so it cannot strengthen the relationship between social factors variables and interest in use. Based on this, it can be concluded that hypothesis 3b is rejected.

Hypothesis 3c: Experience strengthens the relationship between social influence and behavioral intention. The loading factor value of the moderate variable Experience on social factors on interest in use is 0.021 or 0.2%, which means it is positive. The significance value of this path is more than 5%. This means that the moderate variable experience on social factors does not significantly affect interest in use, so it cannot strengthen the relationship between social factors variables and interest in use. Based on this, it can be concluded that hypothesis 3c is rejected.

Hypothesis 3d: Voluntariness of use strengthens the relationship between social influence and behavioral intention. The loading factor value of the moderate variable willingness to use social factors on interest in use is 0.041 or 0.4%, which means it is positive. The significance value of this path is more than 5%. It means that the moderate variable of willingness to use on social factors does not significantly affect interest in use, so it cannot strengthen the relationship between social factors variables and interest in use. Based on this, it can be concluded that hypothesis 3d is rejected.

Hypothesis 4: Facilitating conditions positively and significantly affect Use behavior. The loading factor value of the coefficient of facilitating conditions on usage behavior is 0.007 or 0.07%, which means it is positive. The significance value of this path is more than 5%. It means that the facilitating conditions variable has a positive and insignificant effect on usage behavior. [19]. Based on this, it can be concluded that hypothesis 4 is rejected. Based on the previous descriptive statistical analysis, the indicator on the facilitating conditions variable has a mean of 3.56 with 10 statement items. It shows that students who use IAIN Ponorogo e-learning strongly agree that facilitating conditions or factors can support them using IAIN Ponorogo e-learning for their learning activities.

Hypothesis 4a: Age strengthens the relationship between facilitating conditions and uses behavior. The loading factor value of the moderate age variable in facilitating conditions on usage behavior is 0.044 or 0.4%, which means it is positive. The significance value of this path is more than 5%. It means that the moderate variable age in facilitating conditions does not significantly affect usage behavior, so it cannot strengthen the relationship between facilitating conditions and usage behavior. Based on this, it can be concluded that hypothesis 4a is rejected.

Hypothesis 4b: Experience strengthens the relationship between facilitating conditions and Use behavior. The loading factor value of the moderate variable experience in facilitating conditions on usage behavior is 0.057 or 0.5%, which means it is positive. The significance value of this path is more than 5%. It means that the moderate variable Experience in facilitating conditions does not significantly affect usage behavior, so it cannot strengthen the relationship between facilitating conditions variables and usage behavior. Based on this, it can be concluded that hypothesis 4b is rejected.

Hypothesis 5: Behavioral intention positively and significantly affects use behavior. The loading factor value of the coefficient of interest in use on usage behavior is 0.742 or 74.2%, which means it is positive. The significance value of this path is less than 5%. It means that the user interest variable positively and significantly affects usage behavior. [19]. Based on this, hypothesis 5 is accepted.

Table 8. R-Square Results

Number	Variable	R-Square
1	Z	0.578
2	Y	0.626

In addition to looking at the T-Statistic value, calculations are also carried out by looking at the R2 value, which measures the variability of endogenous constructs that the variability of exogenous constructs can explain. If the R-value is close to 1, it can be interpreted that the independent variable is very supportive of the dependent variable. The following are the R-Square results generated by WarpPLS. Based on Table 8, we can conclude that the R-Square value on the dependent variable behavioral intention is 0.578. It means that the independent variables of performance expectancy, effort expectancy, and social influence can explain the variability of behavioral intention by 57.8%. Meanwhile, the use behavior variable has an R-squared value of 0.626, which means that the independent variables facilitating conditions and behavioral intention can explain the variability of use behavior by 62.6%.

Furthermore, this study was able to identify various factors influence student acceptance of the use of IAIN Ponorogo e-learning. Referring to the research results among the four primary constructs of the UTAUT model, only facilitating conditions have a positive and insignificant effect on usage behavior, indicating user acceptance of IAIN Ponorogo's e-learning.

Facilitating conditions have an insignificant positive effect on use behavior with a parameter coefficient value of 0.7%. Students agree that facilitating conditions are one of the factors that must be improved because these factors affect students' interest in using IAIN Ponorogo e-learning. This finding is in line with Venkatesh et al. [20], who highlighted the role of facilitating conditions in technology adoption. In the online learning media, this could translate to sufficient training and technical support for innovative medical devices.

Behavioral intention positively and significantly influences use behavior, with an estimated value of 0.464 and a t-statistic value of 74.2%. Students strongly agree that interest in utilization or use is one of the factors that must be improved because these factors affect students in using IAIN Ponorogo e-learning. This finding is in line with Kholoud Bajunaied et al. [32] who highlighted behavioral intention to adopt fintech services significantly and positively impacted by performance expectancy, effort expectancy, facilitating condition, and privacy enablers.

CONCLUSION

This study was able to identify various factors that influence the acceptance of e-learning media by students, especially facilitating conditions towards e-learning media that have a positive but insignificant impact on use behavior. Theoretically, this study corroborates the UTAUT acceptance theory that facilitating conditions towards e-learning media has a positive but insignificant impact on usage behavior. From a practical standpoint, the findings on facilitating conditions are important to guide institutions to innovate and develop e-learning as a new learning medium. By engaging with external partners, such as research institutions, and end-users, institutions can leverage diverse knowledge bases, leading to more efficient and user-centred e-learning development [33]. Furthermore, the findings of this study suggest that institutions should conduct socialization and training on the use of the system, summarise the features of e-learning to make it more practical and easy to use, and coordinate with server managers and campus internet network providers to increase bandwidth capacity to make internet connections more stable.

REFERENCES

[1] B. Indrawati, "Tantangan dan Peluang Pendidikan Tinggi Dalam Masa dan Pasca Pandemi Covid-19," *J. Kaji. Ilm.*, vol. 1, no. 1, pp. 39–48, 2020.

[2] P. Donatella, M. Haraldsson, and T. Tagesson, "Reporting on COVID-19 – or not? Annual report disclosure of the pandemic as a subsequent event," *J. Public Budgeting, Account. Financ. Manag.*, vol. ahead-of-p, no. ahead-of-print, Jan. 2021, doi: 10.1108/JPBAFM-04-2021-0074.

[3] B. Tran-Nam, C. Le-Van, and N.-A. Nguyen, "A critical examination of policy objectives and instruments for a sustainable and inclusive post-pandemic recovery," *Fulbright Rev. Econ. Policy*, vol. ahead-of-p, no. ahead-of-print, Jan. 2021, doi: 10.1108/FREP-09-2021-0053.

[4] O. Troisi, G. Fenza, M. Grimaldi, and F. Loia, "Covid-19 sentiments in smart cities: The role of technology anxiety before and during the pandemic," *Comput. Human Behav.*, vol. 126, p. 106986, Jan. 2022, doi: 10.1016/J.CHB.2021.106986.

[5] J. Moosavi, J. Bakhshi, and I. Martek, "The application of industry 4.0 technologies in pandemic management: Literature review and case study," *Healthc. Anal.*, vol. 1, p. 100008, Nov. 2021, doi: 10.1016/J.HEALTH.2021.100008.

[6] W. He, Z. (Justin) Zhang, and W. Li, "Information technology solutions, challenges, and suggestions for tackling the COVID-19 pandemic," *Int. J. Inf. Manage.*, vol. 57, p. 102287, Apr. 2021, doi: 10.1016/J.IJINFOMGT.2020.102287.

[7] I. Irwanto, "Data on undergraduate students' self-regulation in online and blended learning environments during the COVID-19 pandemic in Indonesia," *Data Br.*, vol. 53, p. 110066, 2024, doi: https://doi.org/10.1016/j.dib.2024.110066.

[8] M. Çınar, M. Ekici, and Ö. Demir, "A snapshot of the readiness for e-learning among in-service teachers prior to the pandemic-related transition to e-learning in Turkey," *Teach. Teach. Educ.*, vol. 107, p. 103478, Nov. 2021, doi: 10.1016/J.TATE.2021.103478.

[9] M. Gaudin *et al.*, "E-learning versus face-to-face training: Comparison of two learning methods for Lyme borreliosis," *Infect. Dis. Now*, Nov. 2021, doi: 10.1016/J.IDNOW.2021.11.001.

[10] I. N. Lathifah and I. Wilujeng, "Pengembangan perangkat pembelajaran integrated science berbasis kearifan lokal," *J. Pendidik. Mat. dan Sains*, vol. 4, no. 2, pp. 110–119, 2016, doi: 10.21831/jpms.v4i2.12920.

[11] L.-L. Ung, J. Labadin, and F. S. Mohamad, "Computational thinking for teachers: Development of a localised E-learning system," *Comput. Educ.*, vol. 177, p. 104379, Feb. 2022, doi: 10.1016/J.COMPEDU.2021.104379.

[12] A. Capatina, N. J. Patel, K. Mitrov, D. S. Cristea, A. Micu, and A.-E. Micu, "Elevating students' lives through immersive learning experiences in a safe metaverse," *Int. J. Inf. Manage.*, vol. 75, p. 102723, 2024, doi: https://doi.org/10.1016/j.ijinfomgt.2023.102723.

[13] M. Mukhibat and M. Effendi, "Evaluation of E-Learning on Learning Outcome at Universities in Indonesia," *Educ. Adm. Theory Pract.*, vol. 29, no. 2, 2023.

[14] P. R. Wati, N. Khasanah, and I. F. Sari, "Blended learning and students' engagement," in *UNNES-TEFLIN National Seminar*, 2021, vol. 4, no. 1, pp. 100–110.

[15] R. Donkin and E. Askew, "An evaluation of formative 'in-class' versus 'e-learning' activities to benefit student learning outcomes in biomedical sciences," *J. Biomed. Educ.*, vol. 2017, pp. 1–7, 2017.

[16] A. Rohmanu, E. Muafiah, A. Rahman Hakim, and V. V. W. Damayanti, "Kesiapan, Kompleksitas, dan Harapan Pembelajaran Jarak Jauh: Perspektif Mahasiswa Iain Ponorogo," *Kesiapan, Kompleks, dan Harapan Pembelajaran Jarak Jauh Perspekt. Mhs. IAIN PONOROGO*, vol. 11, no. 2, pp. 221–241, 2020.

[17] Y. Anistyasari and A. I. Nurhidayat, "A Webometric Analysis On State Higher Education Institutions In Indonesia," in *Seminar Nasional Riset Terapan*, 2016, vol. 1, pp. A304–A308.

[18] S. Hadi, "Studies On the Implied Effectiveness of Online Learning Systems in Iain Ponorogo," *J. Qual. Assur. Islam. Educ.*, vol. 1, no. 1, pp. 41–50, 2021.

[19] R. D. Apriyanto and H. P. Putro, "Tingkat Kegagalan dan Keberhasilan Proyek Sistem Informasi di Indonesia," in *Semin. Nas. Teknol. Inf. dan Komun. 2018 (SENTIKA 2018)*, 2018, vol. 2018, pp. 23–24.

[20] Venkatesh, M. . Morris, G. B. Davis, and F. D. Davis, "User Acceptance of Information Technology: Toward A Unified View," *MIS Quartely*, vol. 27, no. 3, pp. 425–478, 2003.

[21] M. B. Rivai, "Penerapan Model the Unified Theory of Acceptance and Use of Technology (UTAUT) untuk memahami Tingkat Penerimaan dan Penggunaan E-Learning (Be Smart) di Fakultas Teknik Universitas Negeri Yogyakarta," Universitas Negeri Yogyakarta, 2014.

[22] W. Khoirunnisak, "Implementasi Model Penerimaan Unified Theory Of Acceptance And User Of Technology (UTAUT) Untuk Menganalisis Faktor-Faktor Penerimaan Dosen Terhadap Penggunaan E-Learning Share-ITS," Institut Teknologi Sepuluh Nopember, 2016.

[23] R. V. Margareta, "Analisis Penerimaan Pengguna Sistem SHARE-ITS Menggunakan Model UTAUT Dengan Menambahkan Dua Variabel Moderat (Jurusan Dan Prestasi Akademik)," ITS Surabaya, 2014.

[24] S. Sarraf, A. K. Kar, and M. Janssen, "How do system and user characteristics, along with anthropomorphism, impact cognitive absorption of chatbots – Introducing SUCCAST through a mixed methods study," *Decis. Support Syst.*, vol. 178, p. 114132, 2024, doi: https://doi.org/10.1016/j.dss.2023.114132.

[25] B. Harnadi, A. D. Widiantoro, and F. X. H. Prasetya, "Investigating the behavioral differences in the acceptance of MOOCs and E-learning technology," *Comput. Hum. Behav. Reports*, p. 100403, 2024, doi: https://doi.org/10.1016/j.chbr.2024.100403.

[26] H. Sharif-Nia *et al.*, "E-learning Acceptance: The Mediating Role of Student Computer Competency in the Relationship Between the Instructor and the Educational Content," *Teach. Learn. Nurs.*, vol. 19, no. 1, pp. e5–e10, 2024, doi: https://doi.org/10.1016/j.teln.2023.08.001.

[27] M. Yao-Ping Peng, Y. Xu, and C. Xu, "Enhancing students' English language learning via M-learning: Integrating technology acceptance model and S-O-R model," *Heliyon*, vol. 9, no. 2, p. e13302, 2023, doi: https://doi.org/10.1016/j.heliyon.2023.e13302.

[28] Y. J. Kim, J. H. Choi, and G. M. N. Fotso, "Medical professionals' adoption of AI-based medical devices: UTAUT model with trust mediation," *J. Open Innov. Technol. Mark. Complex.*, vol. 10, no. 1, p. 100220, 2024, doi: https://doi.org/10.1016/j.joitmc.2024.100220.

[29] G. Jethava and U. P. Rao, "Exploring security and trust mechanisms in online social networks: An extensive review," *Comput. Secur.*, vol. 140, p. 103790, 2024, doi: https://doi.org/10.1016/j.cose.2024.103790.

[30] M. D. Williams, N. P. Rana, and Y. K. Dwivedi, "The unified theory of acceptance and use of technology (UTAUT): a literature review," *J. Enterp. Inf. Manag.*, vol. 28, no. 3, pp. 443–488, 2015.

[31] T. Sihvonen, Z.-S. Duma, H. Haario, and S.-P. Reinikainen, "Spectral Profile Partial Least-Squares (SP-PLS): Local multivariate pansharpening on spectral profiles," *ISPRS Open J. Photogramm. Remote Sens.*, vol. 10, p. 100049, 2023, doi: https://doi.org/10.1016/j.ophoto.2023.100049.

[32] K. Bajunaied, N. Hussin, and S. Kamarudin, "Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology," *J. Open Innov. Technol. Mark. Complex.*, vol. 9, no. 1, p. 100010, 2023, doi: https://doi.org/10.1016/j.joitmc.2023.100010.

[33] L. Dahlander and D. M. Gann, "How open is innovation?," *Res. Policy*, vol. 39, no. 6, pp. 699–709, 2010.