Factors Influencing Acceptance of ILMU E-Learning Among Lecturers: An Empirical Study Based on UTAUT Model

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***Abstract*—*E-learning is a form of innovation in technology used in educational field, including higher education. University of Pembangunan Nasional “Veteran” Jawa Timur is one of many universities that have implemented e-learning called ILMU to support the teaching-learning process. The application of ILMU as e-learning has yet to be utilised by all of the users, in this case lecturers, as a support for the learning process. Meanwhile, successful implementation of a technology requires acceptance from its users. This research was acquited to define the acceptance factors that influence lecturers as users of ILMU e-learning as measured through UTAUT model. The research was carried on by quantitatively distributing questionnaires to 60 lecturers. Data were analyzed and processed using SEM-PLS technique and SMARTPLS 3.0 application. Factors that influence users to receive ILMU e-learning and significantly are effort expectancy, social influence, facilitating conditions, and behavioral intention. Meanwhile, performance expectancy does not influence users significantly to accept ILMU e-learning*.**

***Keywords—*** **E-Learning, Lecturer, User Acceptance, UTAUT**

# Introduction

The rising growth of information and communication technology has led to numerous innovations in a variety of fields. This advancement allows online learning and education to take place. E-learning (electronic learning) is a recent innovation that aims to improve and simplify the educational process for students and teachers in higher-level education.

By definition, e-learning is a form of media that is integrated into an information system and is used for providing learning materials in text, audio, and video which can be produced through online discussions, tasks, quizzes, and email [1]. E-learning has emerged as an appealing complement to conventional methods of learning, as well as a tool to improving learning outcomes [2]. E-learning utilises applying of electronic devices such as computers and tablets to deliver educational and training materials [3]. E-learning is establishing itself as an innovative approach for learning and teaching [4]. E-learning, which is also becoming more popular, provides access, knowledge, easy scheduling, and personalised learning environment [5][6]. With the increasing awareness of the essence of e-learning, many higher-level education entities including University of Pembangunan Nasional “Veteran” Jawa Timur are adopting and implementing this interactive system.

University of Pembangunan Nasional “Veteran” Jawa Timur is one of many universities that uses e-learning in its learning and teaching programmes. The e-learning platform is called ILMU, which serves to improve the learning and teaching processes so that they can take place whenever and wherever they want. Implementation of e-learning at ILMU is emphasized as an alternative to the learning and teaching processes [7]. Students and lecturers both engage in ILMU e-learning that can be utilised by means through a smartphone, laptop, or computer. The use of ILMU e-learning is related to university courses such as material, tasks, or assignments. As one of the few people using ILMU e-learning, lecturer hopes to improve professionalism while carrying out the Three Pillars of Higher Education (Tri Dharma Perguruan Tinggi).

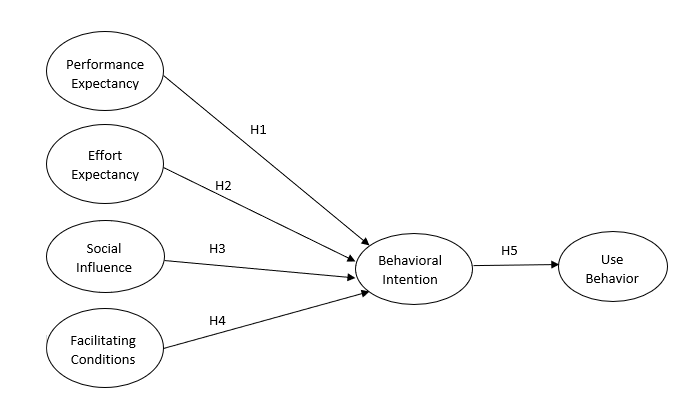
After a few years, e-learning has gained popularity in the education sector due to its usefulness, adaptability, and low cost [8]. E-learning, as a new technology, requires feedback from users, including lecturers. For the lecturers who used e-learning for the first time, e-learning’s functionality is considered new and unfamiliar to them. However, in the development and application of a new technology, it is necessary to consider the user's perspective during its use. User acceptance is defined as the keen interest of a user to implement information technology to assist them in carrying out their duties [9]. As a result, when a user accept a technology, it can predicted the access to knowledge and information, as well as increase one's trust in the advancement of technology [10].

Based on the former explanation, we conducted a research regarding user acceptance towards ILMU in order to understand how successful the implementation of ILMU e-learning is. User acceptance in this research is measured using UTAUT model, which is widely and commonly used to measured user acceptance on technology. By looking at the evaluation variables related to ILMU e-learning, the user acceptance analysis takes place on lecturers who opened ILMU e-learning during the teaching process. With this research, it is expected to find out what factors can impact on user acceptance of ILMU e-learning, particularly among lecturers. It is also to evaluate the features of ILMU e-learning, so lecturers can have better understanding and maximizing its use.

# Methodology

## Conceptual Model

The UTAUT model developed by Venkatesh [11] was used as the conceptual model. This user acceptance model is a more widely used because it can better explicate 70% of the variance in user acceptance by combining 8 previously existing acceptance models [11]. Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, and Use Behavior are the variables in the research model. The conceptual model used is depicted in Fig. 1.



1. UTAUT Conceptual Model

The view that utilising and leveraging technology will improve one's performance is termed to as Performance Expectation. [11]. Users will be provided with a system that enhances their performance [3][12][13]. Meanwhile, Effort Expectancy is the extent or sense of at ease with which a user interacts with a system [11]. Several studies have found that users who recognise a system easy to use are willing to accept it [1][12][13][15].

Social Influence is the feeling that people they regard as important encourage them to use a new system [11]. Users are prone to embrace and acknowledge a system if their peers engage with it [1][12][13][15][16]. The level at which someone believes that technical and operational facilities can maximise the use of technology is described as facilitating conditions. Facility support can improve the usability of a technology so that it is accepted by users [1][3][12][15].

Behavioral Intention can be summed up as the desire of certain person to operate a technology for a certain purpose [1]. User who has the desire to achieve something when using information technology can influence other users to accept this information technology [1][3][14]. Use Behavior is defined as how much and how often users use information technology. Users who frequently use information technology have certainly received and used this information technology in their activities.

Based on the conceptual model and operational definition of each variable, therefore we proposed hypotheses as listed below:

H1: Performance Expectancy significantly impact Behavioral Intention

H2: Effort Expectancy significantly impact Behavioral Intention

H3: Social Influence significantly impact Behavioral Intention

H4: Facilitating Conditions significantly impact Behavioal Intention

H5: Behavioral Intention significantly impact Use Behavior

## Research Methodology

This research is using quantitative methods. This method employs numerical data to measure objective outcomes while conducting statistical analysis [17]. Data was generated from the discoveries of handing out questionnaires to lecturers at UPN "Veteran" Jawa Timur. Questionnaires were distributed to lecturers, as ILMU e-learning users and research objects. Questionnaires are circulated both through online and offline. Online questionnaires are passed around via a Google Form link, while offline questionnaires are handed out directly to lecturers. The questionnaire includes question items according to the variables in the conceptual model. This question was graded on a scale based on five Likert points, with values that vary from firmly opposed (1) to firmly concur (5).

The outcome of the questionnaire distribution are then tested and looked into using a type of Structural Equation Modelling (SEM) technique, namely Structural Equation Modeling-Partial Least Square (SEM-PLS). The SEM technique is a statistical technique for creating and testing causal statistical models [18]. The SEM-PLS method was chosen because it emphasises explaining variance in a research model's dependent variable [19]. A measurement model and a structural model are used in SEM-PLS test analysis. The measurement model points out the association throughout each constructs and the indicators of each construct, as well as how latent constructs can be measured [20]. Meanwhile, the structural model demonstrates how latent constructs are correlated with to one another [20].

# Result And Analysis

The testing results recorded to the data of 60 respondents. These respondents are divided into each faculty proportionally by using purposive sampling technique. The amount of male and female respondents are quite balanced, with 51.7% ofmale lecturers and 48.7% female lecturers as disclosed in Table 1. While in terms of age, the large proportion of the respondents are in the aged of 31-40 years old with 50% percentage. In other age categories, it is shown that lecturers between 22-30 years old have 18.3% percentage, lecturers ranging from 41-50 years old have a percentage of 5%, lecturers between the ages of 51-60 years old have a 16.7% percentage, and lecturers aged over 60 years have a percentage of 10%.

1. Respondents Data

|  |  |  |  |
| --- | --- | --- | --- |
| **Category** | **Type** | **Total** | **Percentage (%)** |
| Gender | Male | 31 | 51.7% |
| Female | 29 | 48.3% |
| Age | 22-30 | 11 | 18.3% |
| 31-40 | 30 | 50% |
| 41-50 | 3 | 5% |
| 51-60 | 10 | 16.7% |
| >60 | 6 | 10% |

1. *Measurement Model*

We conduct measurement model in SEM-PLS method, which includes validity and reliability testing. Validity testing determines whether an instrument can be said to be valid when it is capable to reveal the data of a variable from the actual situation correctly [21]. Meanwhile, reliability testing implies that measurements with similar objects will yield comparable results [22].

Validity testing consists of convergent validity and discriminant validity. Convergent validity is being examined through the outer loading test. While Fornell-Larcker, Cross Loading, and Average Variance Extracted (AVE) are the components of discriminant validity testing. In the other hand, cronbach alpha and composite reliability testing are included in reliability testing. Each validity and reliability test has its own requirements that must be met.

The outer loading value criteria that must be met in the convergent validity test is that the value of each indicator is greater than 0.7 [23]. The results of convergent validity testing in the outer loading test are depicted in Table 2.

1. Preliminary Results of Convergent Validity Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE1** | 0.700 |  |  |  |  |  |
| **PE2** | 0.909 |
| **PE3** | 0.895 |
| **PE4** | 0.900 |
| **PE5** | 0.650 |
| **EE1** |  | 0.541 |
| **EE2** | 0.734 |
| **EE3** | 0.823 |
| **EE4** | 0.834 |
| **EE5** | 0.748 |
| **EE6** | 0.829 |
| **SI1** |  | 0.718 |
| **SI2** | 0.831 |
| **SI3** | 0.733 |
| **SI4** | 0.809 |
| **SI5** | 0.709 |
| **FC1** |  | 0.833 |
| **FC2** | 0.789 |
| **FC3** | 0.906 |
| **FC4** | 0.920 |
| **FC5** | 0.749 |
| **FC6** | 0.698 |
| **BI1** |  | 0.926 |
| **BI2** | 0.946 |
| **BI3** | 0.926 |
| **BI4** | 0.907 |
| **UB1** |  | 0.874 |
| **UB2** | 0.923 |
| **UB3** | 0.944 |
| **UB4** | 0.958 |
| **UB5** | 0.956 |

Table 2 shows that several indicators have a value less than 0.7 based on the criteria that must be met for convergent validity. The PE1, PE5, and EE1 indicators are examples of these indicators. Indicators with values less than 0.7 must be excluded from the research model in order for it to fulfill the convergent validity criteria.

1. Final Results Of Convergent Validity Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE2** | 0.937 |  |  |  |  |  |
| **PE3** | 0.948 |
| **PE4** | 0.959 |
| **EE2** |  | 0.703 |
| **EE3** | 0.806 |
| **EE4** | 0.849 |
| **EE5** | 0.781 |
| **EE6** | 0.859 |
| **SI1** |  | 0.718 |
| **SI2** | 0.831 |
| **SI3** | 0.733 |
| **SI4** | 0.809 |
| **SI5** | 0.779 |
| **FC1** |  | 0.847 |
| **FC2** | 0.837 |
| **FC3** | 0.938 |
| **FC4** | 0.955 |
| **FC5** | 0.739 |
| **BI1** |  | 0.926 |
| **BI2** | 0.946 |
| **BI3** | 0.926 |
| **BI4** | 0.907 |
| **UB1** |  | 0.874 |
| **UB2** | 0.923 |
| **UB3** | 0.944 |
| **UB4** | 0.958 |
| **UB5** | 0.956 |

Table 3 displays that PE1, PE5, and EE1 indicators were all removed. After the indicators were eliminated, the final results indicate that each indicator turned out to well above 0.7, thus fulfilling the convergent validity test.

The Fornell-Larcker test, cross loading, and average variance extracted (AVE) are all required for discriminant validity testing. In the Fornell-Larcker test, each variable is deemed valid if its correlation value with its own construct is exceeding than its correlation value with different constructs.

1. Preliminary Results Of Fornell-Larcker Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE** | 0.948 |  |  |  |  |  |
| **EE** | 0.730 | 0.801 |  |  |  |  |
| **SI** | 0.688 | 0.697 | 0.775 |  |  |  |
| **FC** | 0.275 | 0.333 | 0.388 | 0.866 |  |  |
| **BI** | 0.699 | 0.672 | 0.807 | 0.573 | 0.927 |  |
| **UB** | 0.727 | 0.670 | 0.852 | 0.537 | 0.915 | 0.932 |

The result of the discriminant validity test using the Fornell-Larcker is included in Table 4. The results reveal that correlation between SI and SI is lower than correlation between SI and BI and SI and UB. This demands the removal of construct variables from the correlations between SI and BI and SI and UBThe variable is eradicated by figuring out the biggest average figure between SI and BI, as well as the greatest average figure between SI and UB. The construct variables that must be eliminated based on the calculations are SI4 (0.755), SI5 (0.644), BI2 (0.600), BI3 (0.574), UB1 (0.615), UB3 (0.636), and UB5 (0.608).

1. Final Results Of Fornell-Larcker Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE** | 0.948 |  |  |  |  |  |
| **EE** | 0.728 | 0.802 |  |  |  |  |
| **SI** | 0.564 | 0.583 | 0.821 |  |  |  |
| **FC** | 0.276 | 0.332 | 0.321 | 0.866 |  |  |
| **BI** | 0.640 | 0.657 | 0.644 | 0.558 | 0.946 |  |
| **UB** | 0.736 | 0.681 | 0.633 | 0.506 | 0.847 | 0.964 |

The outcomes of the final test of discriminant validity using the Fornell-Larcker test are presented in Table 5. After eliminating the variables SI4, SI5, BI2, BI3, UB1, UB3, and UB5, the Fornell-Larcker test met the criteria where the correlation of the variable with its own variable is above than the association of the construct with other constructs. Dicriminant validity is considered to meet the criteria so that the research model is said to be valid.

1. Preliminary Results Of Cross Loading Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE2** | **0.936** | 0.685 | 0.586 | 0.283 | 0.609 | 0.702 |
| **PE3** | **0.949** | 0.689 | 0.493 | 0.269 | 0.623 | 0.719 |
| **PE4** | **0.958** | 0.696 | 0.526 | 0.231 | 0.587 | 0.671 |
| **EE2** | 0.398 | **0.693** | 0.333 | 0.381 | 0.365 | 0.416 |
| **EE3** | 0.536 | **0.810** | 0.450 | 0.416 | 0.649 | 0.642 |
| **EE4** | 0.789 | **0.844** | 0.542 | 0.254 | 0.620 | 0.608 |
| **EE5** | 0.566 | **0.787** | 0.474 | 0.072 | 0.434 | 0.487 |
| **EE6** | 0.560 | **0.863** | 0.506 | 0.175 | 0.467 | 0.507 |
| **SI1** | 0.322 | 0.391 | **0.830** | 0.295 | 0.472 | 0.412 |
| **SI2** | 0.540 | 0.479 | **0.894** | 0.188 | 0.640 | 0.563 |
| **SI3** | 0.516 | 0.585 | **0.731** | 0.346 | 0.445 | 0.587 |
| **FC1** | 0.180 | 0.202 | 0.217 | **0.845** | 0.436 | 0.402 |
| **FC2** | 0.264 | 0.198 | 0.161 | **0.837** | 0.330 | 0.266 |
| **FC3** | 0.254 | 0.310 | 0.282 | **0.936** | 0.534 | 0.475 |
| **FC4** | 0.251 | 0.317 | 0.279 | **0.954** | 0.519 | 0.459 |
| **FC5** | 0.243 | 0.362 | 0.396 | **0.743** | 0.529 | 0.515 |
| **BI1** | 0.605 | 0.626 | 0.584 | 0.472 | **0.943** | 0.797 |
| **BI4** | 0.605 | 0.617 | 0.634 | 0.581 | **0.948** | 0.804 |
| **UB2** | 0.733 | 0.648 | 0.587 | 0.459 | 0.746 | **0.958** |
| **UB4** | 0.690 | 0.664 | 0.630 | 0.512 | 0.877 | **0.970** |

The cross loading value, which implies the association of the indicator with its own construct needed to be more than the relation with different constructs, is discovered during discriminant validity testing. This demonstrates an indicator's ability to explain the associated construct when compared to other constructs. The cross loading indicator test results are displayed in Table 6. There are some indicators that don't fulfil the criteria, thus it must be removed. That indicator is EE2.

1. Final Results Of Cross Loading Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PE** | **EE** | **SI** | **FC** | **BI** | **UB** |
| **PE2** | **0.936** | 0.693 | 0.586 | 0.375 | 0.609 | 0.702 |
| **PE3** | **0.949** | 0.714 | 0.493 | 0.364 | 0.623 | 0.719 |
| **PE4** | **0.958** | 0.702 | 0.526 | 0.346 | 0.587 | 0.671 |
| **EE3** | 0.536 | **0.786** | 0.450 | 0.451 | 0.648 | 0.642 |
| **EE4** | 0.789 | **0.853** | 0.542 | 0.362 | 0.620 | 0.608 |
| **EE5** | 0.566 | **0.828** | 0.474 | 0.147 | 0.434 | 0.487 |
| **EE6** | 0.560 | **0.887** | 0.506 | 0.253 | 0.468 | 0.507 |
| **SI1** | 0.322 | 0.409 | **0.830** | 0.349 | 0.472 | 0.412 |
| **SI2** | 0.540 | 0.491 | **0.893** | 0.279 | 0.640 | 0.563 |
| **SI3** | 0.516 | 0.570 | **0.731** | 0.454 | 0.445 | 0.587 |
| **FC1** | 0.180 | 0.158 | 0.217 | **0.825** | 0.435 | 0.402 |
| **FC2** | 0.264 | 0.159 | 0.161 | **0.773** | 0.330 | 0.266 |
| **FC3** | 0.254 | 0.272 | 0.282 | **0.895** | 0.533 | 0.475 |
| **FC4** | 0.251 | 0.279 | 0.279 | **0.909** | 0.518 | 0.459 |
| **FC5** | 0.243 | 0.367 | 0.396 | **0.760** | 0.529 | 0.515 |
| **FC6** | 0.540 | 0.478 | 0.540 | **0.718** | 0.612 | 0.650 |
| **BI1** | 0.605 | 0.630 | 0.584 | 0.574 | **0.945** | 0.797 |
| **BI4** | 0.605 | 0.635 | 0.634 | 0.629 | **0.947** | 0.804 |
| **UB2** | 0.733 | 0.655 | 0.587 | 0.559 | 0.745 | **0.958** |
| **UB4** | 0.690 | 0.665 | 0.630 | 0.606 | 0.877 | **0.970** |

Table 7 depicts the cross loading test results after the EE2 indicator was removed. As a result, the cross loading value of each indicator exceeds than that of the other constructs, indicating that the Fornell-Larcker and cross loading values comply with the discriminant validity criteria.

1. Average Variance Extracted Test Results

|  |  |
| --- | --- |
| Contruct Variable | **Average Variance Extracted (AVE)** |
| **PE** | 0.899 |
| **EE** | 0.705 |
| **SI** | 0.706 |
| **FC** | 0.750 |
| **BI** | 0.894 |
| **UB** | 0.929 |

The Average Variance Extracted (AVE) test is applied in the next discriminant validity test. If the AVE value surpasses or equivalent to 0.5, it complies with the validity criteria [24]. Table 8 shows the AVE value for each construct variable that has a value crosses over 0.5 and is thus proclaimed valid. This means that validity testing, which includes outer loading, Fornell-Larcker, cross loading, and AVE, meets the criteria to qualify as valid.

1. Reliability Test Results

|  |  |  |
| --- | --- | --- |
| Construct Variable | **Cronbach alpha** | **Composite reliability** |
| **PE** | 0.944 | 0.964 |
| **EE** | 0.863 | 0.905 |
| **SI** | 0.793 | 0.878 |
| **FC** | 0.915 | 0.937 |
| **BI** | 0.882 | 0.944 |
| **UB** | 0.924 | 0.963 |

Cronbach alpha and composite reliability are two ways to prove reliability testing. The construct variable value must be greater than 0.7 for both to be declared reliable [25]. Table 9 shows that the Cronbach alpha and composite reliability values for every single construct surpassed 0.7, implies that the model reliable. The research model passes validity and reliability testing, indicating that it is both valid and reliable.

1. *Structural Model*

The analysis of structural model is aims to examine hypotheses. For hypothesis testing, the p-value ought to be lower than 0.05 in order for the hypothesis to be given acceptance. Table 10 conveys the results of hypothesis testing in which four hypotheses are accepted.

1. Hypothesis Test Results

|  |  |  |  |
| --- | --- | --- | --- |
| Construct Variable | **Path Coefficient** | **P-value** | **Results** |
| **PE–BI** | 0.099 | 0.473 | Not Accepted |
| **EE–BI** | 0.239 | 0.036 | Accepted |
| **SI–BI** | 0.415 | 0.000 | Accepted |
| **FC–BI** | 0.355 | 0.004 | Accepted |
| **BI–UB** | 0.847 | 0.000 | Accepted |

The use and acceptance of ILMU as e-learning are unaffected by Performance Expectancy. The existence of ILMU e-learning does not improve overall performance as a lecturer. There are other applications that are more helpful and complementary to the learning process, both in terms of communication, distribution of materials, and student discussions. Other capable applications' performance can undoubtedly support lecturers' performance in teaching, which ILMU e-learning does not provide. As a result, users prefer to use other platforms to support and assist their performance in terms of teaching, assigning, and grading assignments and exams. Previous research also compiled comparable results [16].

Effort Expectancy has a substantial impact on Behavioural Intention in e-learning. As a results of the ease of use of ILMU, users can use e-learning even if they have never utilised a technology platform that helps the teaching process before. Lecturers of various ages prefer e-learning that is simple for them to learn and apply in the learning process. E-learning that is easy to grasp and use will increase the likelihood of using it. A number of prior research studies investigated the effects of e-learning ease of use on usage intentions [1][12][13][15].

Social Influence influences Behavioural Intention as well. One of the reasons for someone using technology is social influence, considering that seeing people in one's social environment, such as friends, family, and relatives, using a particular technology can make one intend to use that technology as well. Users feel the need or desire to use ILMU in the context of ILMU e-learning because their superiors and fellow workers do. These findings correlate with previous research. [1][12][13][15][16].

It has also been demonstrated that Facilitating Conditions affect Behavioural Intention. A person wishes to make use of a new technology due to the fact it is supported both internally and even externally. Internal facilities may include devices such as laptops, cellphones, and internet access for lecturers. Meanwhile, external facilities can take the form of a helpdesk or technicians who can assist lecturers as users in answering questions or resolving problems with technology. Users will use and accept ILMU because there are both internal and external facilities that support it. Several findings are consistent with this research. [1][3][12][15].

Use Behaviour is also contributed by Behavioural Intention. Lecturers who implement ILMU e-learning in the long run because of its convenience and features obtained will use it extensively in the future. The prolonged and maintained use of ILMU e-learning will lead to lecturers accepting ILMU e-learning as a technology. These outcomes concur with preceding studies [1][3][14].

# Conclusion

Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioural Intention were discovered to be factors that influence lecturers as users to accept ILMU e-learning in this research. Users are influenced to accept ILMU e-learning as a consequences of the use of ILMU as e-learning, the current condition of the user's social environment, supporting internal and external facilities, and the intention to use ILMU continuously. While Performance Expectancy has no effect on users who accept ILMU e-learning, interpreting that the use of ILMU as e-learning is still not able to accommodate overall user performance with just one e-learning system, which demands the use of another platform.

This research adds another perspective on lecturers' acceptance of e-learning as users. Additional research can be conducted in the future, by including the perspectives of students as well as other parties who use e-learning in the surroundings of learning. Other variables that may influence the acceptance of e-learning in higher education could be studied further.

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##### References

1. M. Maulida, E. S. Wijaya, & Misnariyani, “Penerapan Model E-Learning Readiness dan UTAUT Untuk Evaluasi Kesiapan dan Penerimaan E-Learning”, Jurnal Teknologi Informasi Universitas Lambung Mangkurat (JTIULM), vol. 6, no. 2, pp. 53 – 60, 2021.
2. S. K. Basak, M. Wotto, & P. Belanger, “E-learning, M-learning and D-learning: Conceptual Definition and Comparative Analysis”, E-Learning and Digital Media, vol. 15, no. 4, pp. 191 – 216, 2018. doi: 10.1177/2042753018785180
3. A. S. Saputra, S. S. Kusumawardani, E. Nugroho, “Pengembangan Model Awal Sistem Evaluasi Penerimaan Pengguna E-Learning Janabadra”, in Seminar Nasional Inovasi dan Aplikasi Teknologi Di Industri, Malang, 4 Februari, 2017. doi: 10.36040/seniati.v3i1.1616
4. M. Marsevani, “The Challenges of E-Learning for Higher Education Lecturers and Learners”, Journal of Education Technology, vol. 6, no. 3, pp. 467 – 477, 2022. doi: 10.23887/jet.v6i3.45537
5. E. Aboagye, J. A. Yawson, & K. N. Appiah, “COVID-19 and E-Learning: The Challenges of Students in Tertiary Institutions”, Social Education Research, vol. 2, no. 1, pp. 1 – 8, 2020. doi: 10.37256/ser.212021422
6. S. Khan, “A Response to “The Perspectives of Educators and Learners on E-Learning: A Cross-Sectional Descriptive Study in a Medical School [Letter]”, Advances in Medical Education and Practice, vol. 12, pp. 1293 – 1294, 2021. doi: 10.2147%2FAMEP.S344184
7. UPT Teknologi Informasi dan Komunikasi (TIK) UPN “Veteran” Jawa Timur, Panduan Aplikasi E-Learning Untuk Dosen, 2018. https://www.upnjatim.ac.id/download/panduan-e-learning/
8. I. Y. Alyoussef, “Acceptance of E-Learning in Higher Education: The Role of Task-Technology Fit with The Informasion Systems Success Model”, Heliyon, vol. 9, no. 3, 2023. doi: 10.1016/j.heliyon.2023.e13751
9. M. Nasir, “Evaluasi Penerimaan Teknologi Informasi Mahasiswa di Palembang Menggunakan Model UTAUT”, in Seminar Nasional Aplikasi Teknologi Informasi (SNATI), 15 Juni, 2018. https://journal.uii.ac.id/Snati/article/view/3006
10. M. J. Pour, M. Hosseinzadeh, M. B. Azar, F. Taheri, “Developing A New Framework For Evaluating E-Learning Systems: Integrating BSC and FAHP”, Kybernetes, vol. 46, no. 8, pp. 1303–1324, 2017. doi: https://doi.org/10.1108/K-02-2017-0060
11. V. Venkatesh, M. G. Morris, G. B. Davis, F. D. Davis, “User Acceptance of Information Technology: Toward a Unified View”, MIS Quarterly, vol. 27, no. 3, pp. 425–478, 2003. doi: 10.2307/30036540
12. I. G. A. Sukarya, I. M. A. Pradnyana, N. Sugihartini, “Analisis Faktor-Faktor yang Mempengaruhi Perilaku Penggunaan Sistem E-Learning Undiksha dengan Model Unified Theory of Acceptance and Use of Technology (UTAUT)”, INSERT: Information System and Emerging Technology Journal, vol. 1, no. 2, 2020. doi: 10.23887/insert.v1i2.25940
13. D. P. Karyaningtiyas, A. Yamin, K. Hermanto, “Analisis Pengaruh Minat Pemanfaatan dan Penggunaan SIAKAD sebagai Media E-learning di Universitas Teknologi Sumbawa”, Jurnal Ilmiah Ilmu Pendidikan (JIIP), vol. 5, no. 8, 2022. doi: 10.54371/jiip.v5i8.783
14. F. Susanto, “Metode Unified Theory of Acceptance and Use of Technology untuk Menentukan Faktor Tingkat Penerimaan Penggunaan E-Learning”, Jurnal Informatika, vol. 19, no. 2, 2019. doi: 10.30873/ji.v19i2.1779
15. H. Agustin, E. Mulyani, “The Acceptance and Use of E-Learning System Among Accounting Lecturers in State and Private Universities in Padang: An Empirical Study Based on UTAUT Model”, in 1st International Conferences On Economics Education, Economics, Business and Management, Accounting and Enterpreneurship (PICEEBA), vol. 37, 2018. doi: 10.2991/piceeba-18.2018.72
16. P. T. Aji, M. Zakarijah, Soenarto, “Faktor-Faktor Yang Mempengaruhi Penerimaan dan Penggunaan E-Learning: Studi Kasus Pembelajaran Jarak Jauh di SMK Ma’arif 1 Yogyakarta”, ELINVO (Electronics, Informatics, and Vocational Education), vol. 5, no. 2, pp. 191 – 198, 2020. doi: 10.21831/elinvo.v5i2.40699
17. Dr. Muh. Yani Balaka, S.E., M.Sc., Agr., Metodologi Penelitian Kuantitatif, Bandung: Widina Bhakti Persada, 2022.
18. Z. N. Amalia, R. W. Ulya, D. R. Hastuti, M. F. F. Mardianto, “Strutural Equation Modeling in Motivation Analysis for Milennial Participation Related to General Elections in Indonesia”, Estimasi: Journal of Statistics and Its Application*,* vol. 2, no. 1, 2021. doi: 10.20956/ejsa.v2i1.12479
19. W. W. Chin, J. –H. Cheach, Y. Liu, H. Ting, X. –J. Lim, T. H. Cham, “Demystifying the Role of Causal-Predictive Modeling Using Partial Least Squares Structural Equation Modeling in Information Systems Research”, Industrial Management & Data Systems*,* vol. 120, no. 12, pp. 2161-2209, 2020. doi: 10.1108/IMDS-10-2019-0529
20. J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P Danks, S. Ray, “Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook”, Switzerland: Springer, 2021. doi: 10.1007/978-3-030-80519-7
21. S. Arikunto, Prosedur Penelitian: Suatu Pendekatan Praktik, Jakarta: Rineka Cipta, 2018.
22. Sugiyono, Metode Penelitian Kuantitatif, Kualitatif dan R&D, Bandung: Alphabet, 2019.
23. U. Sekaran, R. J. Bougie, Research Methods for Business: A Skill Building Approach, 7th Edition, New York: John Wiley & Sons Inc, 2016.
24. J. Hair, M. Sarstedt, L. Hopkins, V. Kuppelwieser, “Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool for Business Research”, European Business Review, vol. 26, no. 2, pp. 106 – 121, 2014. doi: 10.1108/EBR-10-2013-0128
25. W. W. Chin, “The Partial Least Squares Approach to Structural Equation Modeling”, Modern Methods for Business Research, pp. 295 – 336, 1998.