Determinants of Lectures’ E-learning Usage in Universitas Negeri Yogyakarta Based on Extended Technology Acceptance Model

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Abstract. Several studies have suggested that behavioral and social factors influence the implementation of e-learning apart from technological mechanisms. Therefore, this study aims to prove the significance of these factors related to the acceptance and use of e-learning by lecturers at Universitas Negeri Yogyakarta. This study used a modified Technology Acceptance Model (TAM) by including four additional constructs, namely job relevance, coercive pressure, mimetic pressure, and normative pressure. This ex post facto study administered an online survey to collect data from lecturers at Universitas Negeri Yogyakarta who have used e-learning, represented by Faculty of Engineering, Faculty of Education, Faculty of Language and Arts, Faculty of Social Sciences, Faculty of Mathematics and Natural Sciences, and Faculty of Sports Science. The data were analyzed using the partial least square (PLS) approach. The findings indicated that first, the strongest determinants of perceived usefulness were the variables of perceived ease of use and mimetic pressure, then followed by variables of normative pressure, job relevance, and coercive pressure. Second, the factors that influence behavioral intention are variables of perceived usefulness, job relevance, and perceived ease of use. Meanwhile, the coercive pressure variable was not proven to affect behavioral intention. Third, the factor that has a significant influence on actual usage is behavioral intention. This study mainly demonstrated that the strongest aspect influencing lecturers to use e-learning was the intention to use. Meanwhile, the strongest aspects that influence the intention to use are perceived benefits, followed by job relevance, and ease of use.

1. Introduction

The use of technology in the learning process is increasing along with the development of information and communication technology (ICT). ICT has been used at every level of education since it is beneficial for the education system to provide quality education [1]. The use of ICT is confirmed to increase the effectiveness and efficiency in completing work which further has a positive impact on the performance of educators [2]. In other words, the rapid development of ICT encourages the development of better information services in education. The use of ICT in the learning process can be accomplished in various forms, including online teaching materials, learning media applications, and a learning management system (LMS). One of the roles of ICT as a provider of learning is called electronic learning (e-learning) [3].

Furthermore, e-learning is a learning process through the use of technology or the internet. Apart from focusing on the use of technology, e-learning also leads to students’ involvement in learning, thus creating learning collaboration between students and teachers [4]. In its application, the e-learning process requires students to learn independently following the direction designed by the teacher. In addition, teachers must be able to develop the potential of students through the existing learning process. The availability of adequate facilities and administrators who can store all learning data is compulsory in the e-learning process.
Currently, the concept of e-learning has been widely accepted by the world community, as indicated by the widespread implementation of e-learning in educational institutions (schools, training institutes, and universities) and industry. According to elearningindustry.com data, the online education industry in Indonesia ranks 8th in the world based on the number of e-learning market requests each year which is 25 percent. It is higher than the average in Southeast Asia of 17.3 percent. Indonesia, China, America, India, and Brazil have promising opportunities in 2017 [5].

Since 2006, Universitas Negeri Yogyakarta (UNY) has developed e-learning called BeSmart with the URL http://besmart.uny.ac.id/v2. There have been various efforts to promote and encourage e-learning, both technologies, and lecturer training. The lecturer training program is carried out every year. However, in fact, not all lecturers use e-learning for the learning process. It was reported from the UNY e-learning site (http://besmart.uny.ac.id/v2), the acceptance of e-learning by UNY lecturers was unpromising since it was used by only 43% of lecturers.

On a broader scale, the rank of e-learning readiness in Indonesia still lags behind the neighboring countries such as Malaysia and Singapore. In 2010, Indonesia was ranked 65th out of 70 countries, while Malaysia and Singapore were ranked 38th and 8th (EIU & IBM, 2010: 4). In 2015, Indonesia was ranked 79th out of 143 countries, while Malaysia and Singapore were ranked 32 and 1 [6]. This condition revealed that it was difficult to meet the target achievement of the Ministry of Education and Culture's Strategic Plan. Therefore, the competitiveness of Indonesia in the field of ICT is still relatively low.

This situation in UNY and Indonesia reflects the low level of acceptance of e-learning technology in developing countries. Several critical success factors that influence the acceptance of e-learning systems in developing countries consist of three main dimensions: system dimensions, personal dimensions, and environmental dimensions [7]. In addition, e-learning is also a socio-technical system that has a technical system and a social system [8]. Therefore, to increase the level of acceptance of e-learning in UNY, a non-technology approach is required, namely an organization in which there is a human element (lecturer) as the main actor in e-learning users.

This study adopts the Technology Acceptance Model (TAM) by adding external variables from organizational elements including the constructs of job relevance, coercive pressure, mimetic pressure, and normative pressure. In general, this study explores the direct and indirect influence of organizational elements on the acceptance of the use of e-learning by lecturers in UNY. Furthermore, this study analyzes: (1) how much does job relevance influence perceived usefulness, (2) how much does coercive pressure influence perceived usefulness, (3) how much does mimetic pressure influence perceived usefulness, (4) how much does normative pressure influence perceived usefulness, (5) how much does perceived ease of use influence perceived usefulness, (6) how much does job relevance influence behavioral intention, (7) how much does coercive pressure influence behavioral intention, (8) how much does perceived usefulness influence behavioral intention, (9) how much does perceived ease of use influence behavioral intention, (10) how much does behavioral intention influence the actual usage of learning.

2. Research Method

2.1. Types of research and data collection techniques

This study is an ex post facto study with a quantitative approach. The objective of this study was to determine the factors that influence the implementation of e-learning by lecturers at UNY and to examine the relationship between the variables. To achieve these objectives, the respondents' perceptions of other variables considered to have significant influence is measured.
The study was conducted in UNY for lecturers who had used e-learning. The research sample consisted of 84 lecturers selected randomly to represent each faculty in UNY, including Faculty of Engineering, Faculty of Education, Faculty of Language and Arts, Faculty of Social Sciences, Faculty of Economics, Faculty of Mathematics and Natural Sciences, and Faculty of Sports Science. The primary data source in this study was collected from UNY lecturer respondents who used BeSmart e-learning. The form of the instrument used to measure the variables in this study was a questionnaire. It was a closed questionnaire by choosing an alternative that best suits the respondents. Alternative answers in the questionnaire used a Likert scale with four options. The questionnaire was distributed online using Google Form.

2.2. Instrument validity testing

The validity of the instruments provided in this study was the content and construct validity. The content validity test was performed by formulating an instrument grid then asking for expert opinion (expert judgment), through Focus Group Discussion by the members of the Research Group team. The FGD was used to assess that the statement items in the instrument can represent all aspects or variables being measured.

After obtaining input from the FGD, then the revised instrument was tested in a field trial to evaluate the construct validity. The field trial was carried out on 30 respondents outside the research sample. The construct validity testing was performed by correlating the score of each statement item with the total score of the item through the product-moment correlation with a significant level of 5%. If the correlation is positive with a minimum coefficient of 0.3 then the item will be a strong construct. Conversely, if the correlation is negative with a minimum coefficient of 0.3 then the factor will be classified as invalid and, consequently, the factor must be removed. Based on the test results, all constructs satisfy the validity requirements.

2.3. Data analysis technique

This study used a partial least square (PLS) approach to analyze the data. Data analysis was performed using SmartPLS software. The stages of data analysis included: designing the Structural Model (Inner Model), designing the Measurement Model (Outer Model), evaluating the Outer Model, evaluating the Inner Model, and testing the hypothesis (Resampling Bootstrap).

3. Results and Discussions

3.1. Inner Model Design

The inner model describes the relationship between Latent Variables based on the theory and the proposed research hypothesis. Based on the proposed hypothesis, 8 constructs consist of 5 exogenous constructs and 3 endogenous constructs. Exogenous constructs include job relevance (JR), coercive pressure (CP), mimetic pressure (MP), normative pressure (NP), and perceived ease of use (PeoU). Meanwhile, endogenous constructs include perceived usefulness (PU), behavioral interest (BI), and actual usage (AU). Furthermore, the inner model is designed using SmartPLS software which can be seen in Figure 1. Figure 1 shows that the latent variables JR, CP, MP, NP, and PeoU are exogenous latent variables ($\xi$), namely independent variables that are not influenced by other variables in the model. Meanwhile, BI and AU latent variables are Endogenous latent variables ($\eta$), which are variables that can be influenced by one or more other variables.
3.2. Outer model design

The outer model illustrates the relationship between the observed variable and the latent variable. The outer model design determines the observed variable properties of each latent variable based on the operational definition of the research variables. The nature of the observed variable of each latent variable is reflective, thus the direction of the arrow is from the latent variable to the observed variable. The Outer model was designed using SmartPLS software presented in Figure 2.

3.3. Evaluate the Outer Model

The outer reflective model was evaluated using three criteria, namely convergent validity, discriminant validity, and composite reliability. Convergent validity can be seen from the correlation between each observed variable and the latent variable which is called factor loading. To meet convergent validity criteria, factor loadings should be greater than 0.7. The results of the model estimation using the PLS Algorithm is described in Figure 3. Figure 3 shows that there is no indicator with a loading factor below 0.7. This shows that all observed variables for each latent variable have fulfilled the convergent validity.
Discriminant validity of the outer model can be seen in the output cross-loading between the observed variable and the latent variable in Figure 4. The output presented in Figure 5 indicates that the factor loading value of each observed variable with each latent variable is higher than the factor loading value with the latent other variables. This suggests that the latent variable predicts the observed variable on its factor better than the observed variable on other latent variables.

Figure 3. The Outer Model Estimation Results

Figure 4. Cross Loading Value
Furthermore, the value of composite reliability can be seen in the output construct reliability and validity. The construct is declared reliable if the composite reliability and Cronbach's alpha values are above 0.70 [9]. The output composite reliability and Cronbach's alpha of the model can be seen in Table 1.

| Latent Variable | Composite Reliability | Cronbach Alpha |
|-----------------|-----------------------|----------------|
| JR              | 0.871                 | 0.780          |
| CP              | 0.821                 | 0.704          |
| MP              | 0.944                 | 0.912          |
| NP              | 0.929                 | 0.884          |
| PPeU            | 0.915                 | 0.884          |
| PU              | 0.918                 | 0.888          |
| BI              | 0.947                 | 0.917          |
| AU              | 0.911                 | 0.869          |

Table 1 shows that the composite reliability value of all latent variables is above 0.9 so that it meets the criteria for being reliable. Furthermore, the Cronbach alpha value of each latent variable is above 0.70, so it can be concluded that each latent variable in the evaluated model has good reliability.

3.4. Inner model evaluation

Inner Model evaluation is conducted by looking at the R-square (R2) value, the higher the R-square (R2) value, the greater the ability of the Exogenous Latent Variable to explain the Endogenous Latent Variable thus the Inner Model is improving. The R-square (R2) value of each endogenous Latent Variable is presented in Table 2.

| Latent Variable | R-Square (R2) |
|-----------------|---------------|
| PU              | 0.721         |
| BI              | 0.667         |
| AU              | 0.716         |

Based on Table 2, the R-square (R2) value of the endogenous latent variable PU, BI, and AU can be explained as follows: (1) in the first model, the R-square (R2) value of the endogenous latent variable PU is 0.721 so that the model is in a good category. This means that the exogenous latent variables JR, CP, MP, NP, and PPeU can explain the latent variable PU by 72.1%, and the rest is explained by other variables not examined in this model. (2) in the second model, the R-square (R2) value of the latent BI endogenous variable is 0.667 so that the model is in a good category. This means that the latent variables JR, CP, PU, and PPeU can explain the BI latent variable by 66.7% and the rest is explained by other variables outside the model. (3) in the third model, the R-square (R2) value of the AU endogenous variable latent is obtained at 0.716 so that the model is in a good category. This means that the latent variable BI can explain the latent variable AU by 71.6%.

3.5. Hypothesis testing results

Hypothesis testing between constructs, namely the exogenous construct against the endogenous construct (γ) and the endogenous construct against the endogenous construct (β) was performed by using the bootstrap resampling method by measuring the path coefficient value. If the coefficient value is statistically significant, the hypothesis is accepted. In this study, 10 hypotheses were tested, if the t-value> 1.96 (for 2-tailed testing) which is equivalent to p <0.05, then the hypothesis is accepted [10]. The results of hypothesis testing are explained in Figure 5.
Based on the results of hypothesis testing in Figure 5, it can be seen that there are 9 accepted hypotheses and 1 rejected hypothesis. The test results include: (1) The path coefficient of BI on AU has the highest effect value with a total of 0.820, which means that there is a positive influence on behavioral intention on the actual usage of e-learning; (2) The PU path coefficient towards BI has a value of 0.471, which means that there is a positive influence on perceived usefulness on behavioral intention; (3) The MP path coefficient on PU has a value of 0.289 which means that there is a positive effect of mimetic pressure on perceived usefulness; (4) The PeoU path coefficient on PU has a value of 0.284 which means that there is a positive effect of perceived ease of use on perceived usefulness; (5) The JR path coefficient towards BI has a value of 0.254 which means the positive effect of job relevance on behavioral intention; (6) The NP path coefficient on PU has a value of 0.231 which means that the positive effect of normative pressure on perceived usefulness; (7) The PeoU path coefficient towards BI has a value of 0.202, which means that there is a positive effect of perceived ease of use on behavioral intention; (8) The JR path coefficient towards PU has a value of 0.172 which means that there is a positive effect on job relevance for perceived usefulness; (9) The CP path coefficient on PU has a value of 0.171 which means that there is a positive effect of coercive pressure on perceived usefulness. Meanwhile, the results of testing the effect of CP on BI were rejected because the statistical T value was lower than the T table value and the p value > 0.005, so it was proven that there was no effect of coercive pressure on behavioral intention.

3.6. Discussion

3.6.1. The determinant of perceived usefulness

Factors proven to influence perceived usefulness are variables of perceived ease of use, mimetic pressure, normative pressure, job relevance, and coercive pressure. Based on the research results, the variables of perceived ease of use and mimetic pressure are the strongest determinants of perceived usefulness compared to the variables of normative pressure, job relevance, and coercive pressure. Perceived ease of use is a level where someone believes that the use of a particular system can reduce one's effort in doing something [11]. This means that user confidence not to require a lot of effort when using a system can affect the level of its use, in other words, the higher the perceived ease of use, the better the level of e-learning usage. This finding is in line with other studies that state that ease of use can increase the acceptance of technology used in learning [12]. Meanwhile, mimetic pressure illustrates that using technology is considered to increase one's status in the social system [13]. This implies that the higher the surrounding pressure in using e-learning, which can increase prestige, will increasingly affect lecturers in using e-learning.
3.6.2. The determinant of behavioral intention

Factors that influence behavioral intention are the variables of perceived usefulness, job relevance, and perceived ease of use. Based on the research findings, the strongest determinant of behavioral intention is perceived usefulness. Perceived usefulness can be defined as a level where a person believes that a system can improve the user's performance of the system [11]. This means that higher user's belief that e-learning can improve performance will stimulate the desire to use it more. Another variable that is proven to affect behavioral intention is job relevance. Job relevance is an individual's perception of targets that can be set according to their job [14]. This means that perceptions about the usefulness of e-learning can be influenced by the suitability of the user's job target with the consequences of using e-learning (job relevance). Furthermore, the variable of perceived ease of use is also proven to affect behavioral intention but not as much as the effect of perceived usefulness. This is in accordance with the theory that perceived usefulness greatly influences moral intention, whereas perceived ease of use only has a small but significant effect on behavioral intention [15].

Meanwhile, the coercive pressure variable was not proven to affect behavioral intention. This result is not in accordance with the theory that coercive pressure can support the use of a system or technology, this is because the coercive pressure of using e-learning at UNY has not been fully established in official regulations. The existing studies stated that coercive pressure in the form of regulation has the greatest influence compared to mimetic pressure [16].

3.6.3. The determinant of actual usage of e-learning

This study showed that the behavioral intention variable has a considerable influence on the actual usage variable. This means that the intention to use can affect the level of e-learning usage in accordance with the TAM theory [11][14]. Furthermore, the results of the path analysis as a whole can show that the strongest aspect influencing lecturers to use e-learning is the intention to use. Meanwhile, the strongest aspects that influence the intention to use are perceived benefits, followed by job relevance, and ease of use.

4. Conclusions

This study tested extended TAM by including four additional variables, namely job relevance, coercive pressure, mimetic pressure, and normative pressure. The model was evaluated using data collected from lecturers using BeSmart e-learning at Universitas Negeri Yogyakarta. Several results of this study are: first, the factors that influence perceived usefulness are the variables of perceived ease of use, mimetic pressure, normative pressure, job relevance, and coercive pressure. Furthermore, the variables of perceived ease of use and mimetic pressure are the strongest determinants of perceived usefulness compared to the variables of normative pressure, job relevance, and coercive pressure. Second, the factors that have been shown to influence behavioral intention are the variables of perceived usefulness, job relevance, and perceived ease of use. Meanwhile, the coercive pressure variable was not proven to affect behavioral intention. This is because the coercive pressure for using e-learning at YSU has not been fully established in official regulations so that there is no strong pressure for lecturers to use BeSmart. Third, the factor that has a significant influence on actual usage is the behavioral intention, which means that intention to use can affect the level of e-learning usage.
5. References

[1] F. Mikre, “The Roles of Information Communication Technologies in Education: Review Article with Emphasis to the Computer and Internet,” *Ethiop. J. Educ. Sci.*, no. July, 2011.

[2] B. Destiana and S. Soenarto, “Faktor Determinan Pemanfaatan TIK dan Pengaruhnya terhadap Kinerja Guru SMK di Kabupaten Gunungkidul,” *J. Pendidik. Vokasi*, vol. 4, no. 3, Nov. 2014.

[3] Priyanto, 2017, “E-Learning Sebagai Sistem Sosio-Teknis : Strategi Pengembangan E-Learning Di Pendidikan Vokasi,” no. February, pp. 163–169, 2017.

[4] F. Bacao, “E-learning concept trends E-learning Concept Trends,” no. July, 2013.

[5] Dian Anditya Mutiara, “Indonesia Menempati Urutan ke-8 untuk Kebutuhan E-Learning,” 2020. [Online]. Available: https://wartakota.tribunnews.com/2017/12/09/indonesia-menempati-urutan-ke-8-untuk-kebutuhan-e-learning. [Accessed: 11-Jul-2020].

[6] K. Schwab, “The Global Competitiveness Report 2015–2016: Full Data Edition,” the World Economic Forum, 2015.

[7] W. Bhuasiri, O. Xaymoungkhoun, H. Zo, J. J. Rho, and A. P. Ciganek, “Critical success factors for e-learning in developing countries: A comparative analysis between ICT experts and faculty,” *Comput. Educ.*, vol. 58, no. 2, pp. 843–855, 2012.

[8] K. T. Upadhya and D. Mallik, “E-Learning as a Socio-Technical System: An Insight into Factors Influencing its Effectiveness,” *Bus. Perspect. Res.*, vol. 2, no. 1, pp. 1–12, Jul. 2013.

[9] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, “Multivariate data analysis: International version,” *New Jersey*, Pearson, 2010.

[10] J. F. Hair Jr, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, “Partial least squares structural equation modeling (PLS-SEM),” *Eur. Bus. Rev.*, vol. 26, no. 2, pp. 106–121, Mar. 2014.

[11] F. D. Davis, “Perceived usefulness, perceived ease of use, and user acceptance of information technology,” *MIS Q. Manag. Inf. Syst.*, vol. 13, no. 3, pp. 319–339, 1989.

[12] Y. Zhonggen and Y. Xiaozhi, “An extended technology acceptance model of a mobile learning technology,” *Comput. Appl. Eng. Educ.*, vol. 27, no. 3, pp. 721–732, 2019.

[13] G. C. Moore and I. Benbasat, “Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation,” *Inf. Syst. Res.*, vol. 2, no. 3, pp. 192–222, Sep. 1991.

[14] Viswanath, Venkatesh and Fred D., Davis, “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies,” *Manage. Sci.*, vol. 46 (2), no. 2, pp. 186–204, 2000.

[15] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models,” *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989.

[16] A. J. Chen, R. T. Watson, M.-C. Boudreau, and E. Karahanna, “An Institutional Perspective on the Adoption of Green IS & IT,” *Australas. J. Inf. Syst.*, vol. 17, no. 1, Nov. 2011.