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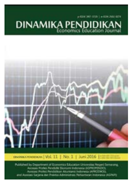

E-Learning Adoption: How Is Students Behavior During The Covid-19 Pandemic?

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Abstract

This study aims to analyze the factors that influence the acceptance and behavior of using e-learning students of the Faculty of Economics, Universitas Negeri Semarang during Covid 19. This study adopted five elements that make up the modeling of UTAUT 2. This study is a quantitative study. The sample in this study were 351 students and used a questionnaire in data collection. The data analysis technique used Structural Equation Models. The results of this study reveal that performance expectancy, hedonic motivation, and habit directly affect the behavioral intentions of students in using e-learning. Habit and behavioral intentions have a direct effect on student behavior in using e-learning. Performance expectancy, hedonic motivation and habit indirectly influence user behavior through students' behavioral intention in using e-learning. Habit is the variable that most plays a role in explaining student behavior in adopting e-learning when compared to other variables in this study. The conclusion of this study is that performance expectations, hedonic motivation, habits and behavioral intentions determine student behavior in adopting e-learning during Covid 19.

How to Cite

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INTRODUCTION

The spread of the Covid-19 has caused major changes to education. The Ministry of Education and Culture issued a Circular Letter of the Ministry of Education and Culture number 4 of 2020 concerning the Implementation of Education Policies in the Emergency Period for the spread of Covid-19 which was carried out remotely. Higher education institutions such as universities must be faced with decisions on how to continue the learning and teaching process while maintaining the safety to educators, staff and students. This situation has certainly pushed almost all educational institutions towards online learning, although not a few educational institutions are not ready run with this transition.

The internet rapid development has eroded the boundaries of space and time in the world of education so the students can continue the learning process with a distance learning system with technology (Tan, 2013). E-learning is considered as one of the most revolutionary tools for higher education institutions because it can be used widely and globally (Salloum & Shaalan, 2018; Wardoyo, 2016). Most educational institutions have turned to online learning platforms to keep academic activities running (Muthuprasad, et. al., 2021). The Covid-19 pandemic has raised the students concerns on the quality of learning, effectiveness, learning outcomes and student satisfaction (Baber, 2021). The implementation of e-learning from various parties considers that it is still not optimal in terms of design, readiness and effectiveness (Muthuprasad, et. al., 2021).

Basically the purpose of e-learning is to increase learning effectively (Alshehri, et. al., 2019). Students in e-learning use various platforms like elena, zoom meeting, goggle meet and google class room. Currently e-learning has an important role to facilitate the implementation of learning online. However, the use of e-learning still needs to be evaluated, especially from the user side. Previous research stated that e-learning needs to be evaluated to ensure of its presence can be utilized optimally (Syafri & Rafli, 2019).

This of course raises various user perspectives, especially from students. One of the determining factors for the successful application of technology information is the attitude of users who use technology. Continuous using is considered a measure of success in the implementation of information systems (Bakar, et. al., 2013). Further investigation of the behavioral intentions of users of e-learning systems is very important to determine the successfull of educational institutions as measured by the behavior and intentions of students and educators in adopting information systems (Tarhini, et. al., 2017).

The purpose of this study is describing the factors that influence the acceptance and behavior of using e-learning by Universotas Negeri Semarang (UNNES) students. The researcher uses the Unified Theory of Acceptance and Use of Technology (UTAUT 2) model which is considered very good to measure the success factors in determining the behavior of e-learning users. Rahman, et. al., (2021) stated that UTAUT 2 is a complete and consistent model that can be analyzed contextually and applied more broadly than a theory.

Tan (2013) stated that performance expectations, business expectations, and social influences have a positive effect toward behavioral intentions and facility conditions, furthermore behavioral intentions also have a positive effect on usage behavior. Furthermore, Tarhini, et.al, (2017) performance expectancy, social influence, habit, hedonic motivation, self-efficacy, effort expectancy and trust have a strong influence on behavioral intentions. Further findings Samsudeen & Mohamed, (2019) stated that the UTAUT construction had a significant impact and played an important role in students' behavior to use e-learning.

The benefit and student rate satisfaction as e-learning users still as the essence of questions in e-learning (Salloum & Shaalan, 2018). To solve this challenges and increase user acceptance, it is important to identify the underlying reasons people why accept or reject the technology. So this is certainly a gap for researchers to further investigate the Unified Theory of Acceptance and Use of Technology (UTAUT 2) to prove how user behavior determines student success in online learning during the pandemic.

In addition, there are the results that show the inconsistency of the UTAUT 2 in explaining user behavior. Effort expectancy has no effect on behavioral intention (Salloum & Shaalan, 2018); expectations, facilitating conditions and price value have no effect on behavioral intention Tarhini, et.al. (2017) performance expectancy, and motivation have no significant effect on behavioral intention (Bakar, et. al., 2013). Venkatesh, et.al (2003) developed the UTAUT model then finally Venkatesh et al. (2012) coined the latest model UTAUT 2, which was originally used to measure consumer behavior. This model tests the previous UTAUT model by adding three new variables into the UTAUT 2 model, those are hedonic motivation, price value, and habit and adding three moderating variables, namely age, gender, and experience.

The theory of UTAUT 2 nowadays is considered the most relevant in predicting behavioral intentions and user behavior (Yuan, et. al., 2015; Kang, et. al., 2015; Morosan & De Franco, 2016). In predicting user behavior in e-learning adoption, it is very appropriate to use UTAUT 2 modeling. This study adopts five elements that make up the modeling of UTAUT 2, namely performance expectancy, habit, hedonic motivation, behavioral intention and user behavior. The adoption of five variables that will be used as research modeling is based on the characteristics that often appear in e-learning users, especially students, so these variables need to be investigated.

Vankatesh, et.al (2003) defined performance expectancy as the degree of the person who believes that using the system will help gain an advantage in improving job performance. Furthermore, performance expectancy can be interpreted as the extent in which the using technology will provide benefits to consumers and lead to increased performance (Brown, et al., 2016). Performance expectancy is the strongest factor of behavioral intention to use mobile applications (Chong, 2013). When users find useful applications, they will have a higher intention to use mobile applications (Hew, 2015).

Previous research has stated that there is a positive and significant relationship between performance expectancy and behavio-

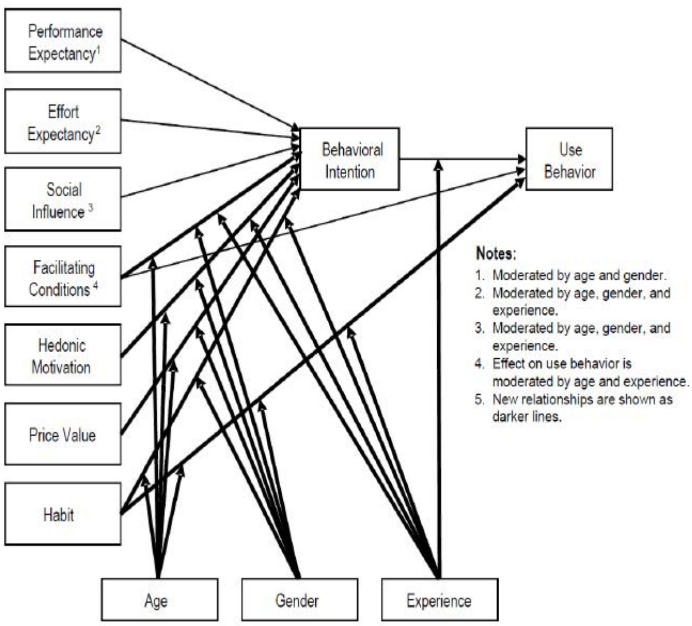

Figure 1. UTAUT 2 model (Venkatesh, et. al. 2012)

ral intentions (Oliveira, et al., 2016; Slade, et al., 2015; Yuvaraj, 2016; Mittal, et.al., 2021). Furthermore, performance expectancy has the greatest impact on behavioral intentions to use contact-tracing apps (Ezzaouia, & Bulchand, 2021). Performance expectancy can be measured using several indicators, namely perceived usefulness, job-fit, relative advantages (Venkatesh, et. al, 2003 & Venkatesh, et. al, 2012).

In the UTAUT 2 construct, there is also a hedonic motivational construct which is pleasure in using technology (Venkatesh., et.al., 2012). Hedonic motivation in several studies plays an important role in determining a person's intention to e-learning (Tarhini, et.al., 2017; Ain, et.al., 2016). Therefore, if students feel happy in using the e-learning system, then they will be more likely to use the system frequently and long term (Samsudeen & Mohamed, 2019). Previous research has found a positive and significant relationship between hedonic motivation toward behavioral intention (Nikolopoulou, et.al., 2020; Alalwan, et.al., 2017; Hew, 2015). Hedonic motivation plays a very important role in shaping the decision to adopt telebanking (Alalwan, et.al., 2016). The indicators that can be used to measure hedonic motivation based on Venkatesh (2012) are the system is fun, the system is enjoyable, the system is very entertaining.

Price value is defined as the consumer's cognitive exchange between the perceived benefits of the application and the monetary cost using (Venkatesh, et.al., 2012). Baabdullah, (2018) explained that someone will tend to consider the price level that they have paid and the value of the benefits they may get from using the technology. Kwateng, et.al., (2019) also said in the Education context will be more concerned with the perceived benefits of the price paid, so the private value affects the intention in technology using . According to Venkatesh, et.al., (2012) price value is measured by indicators that are reasonably priced, value for money, provide a good value.

Habit is the extent the people to tend the perform behavior automatically due to learning (Venkatesh, et.al., 2012). Furthermore, habits are closely related to automatic behavior, which is formed by a collection of experiences, knowledge, and skills (Venkatesh, et.al., 2012). This means that someone who uses technology will form a habit that will gradually form behavior automatically (Tarhini, et.al., 2015). In education context, students will be more likely to use e-learning because they already have the ability to use smartphones, so students are easier to operate the system because they have learned from previous experiences.

Previous research has confirmed that habit has an effect on behavior intention, and even has an effect on user behavior through behavior intention (Gunasinghe, et.al., 2019). In addition, habit plays a significant role in influencing the adoption of cellular banking (Kwateng, et.al., 2018). While other studies have confirmed that habit is the most important predictor and a very strong relationship to influence behavioral intention (Nikolopoulou, et.al., 2020; Chua, et al., 2018; Alshehri, et.al., 2019). Habit can be measured through several indicators, videlicet: use system has become a habit, addicted to using system, must use system (Venkatesh, et.al., 2012).

In the UTAUT model, behavioral intentions are an accumulation of attitudes, subjective norms, perceived behavioral control that generates intentions that are able to generate behavioral intentions (Alshehri, 2019). Behavioral intention has become a direct antecedent of actual use. In fact, behavioral intentions play a central role in predicting an individual's actual use of an information system. In various models of technology acceptance and showing individual actions to use certain technologies, behavior intention is an important factor to consider (Sezgin & Yildirim, 2016). Behavioral intention in the context of education means that the user's desire to accept the e-learning system (Salloum and Shaalan, 2018). Someone will consider certain aspects to determine his intention to use an e-learning system from existing learning methods to the future.

The UTAUT model user behavior is

positioned as an endogenous variable where user behavior is influenced by behavioral intentions of a technology. The UTAUT and UTAUT 2 models are the underlie formation of strong relationship between behavior intention and user behavior. Previous research has stated that behavioral intentions affect to user behavior (Lin & Lai, 2019; Batoro, 2020; Purwanto & Loisa, 2020; Widhiastuti & Yulianto, 2017; Tak & Panwar, 2017). While other findings stated that behavioral intentions have succeeded becoming a mediator that connects the UTAUT 2 construct to user behavior (Gupta, 2018). Behavioral intention acts as a variable mediator which will have a stronger influence in actual use of e-learning (Chao, 2019; Fagan, 2019; Sidik and Syafar, 2020).

The UTAUT 2 model has been developed by Venkatesh et al. (2012) which is involved three moderating variables, namely age, gender and experience. According to Venkatesh et.al. (2012) said that age is a description of individual maturity in taking action. Increasing a person's age has been shown to affect his ability to use or receive information that usually required when using a system. Venkatesh et.al. (2012) defined the gender as the biological differentiation of individuals. Gender will have an impact to acceptance and technology. According to Venkatesh (2012) experience is a condition that has been carried out by individuals and as a guide for future actions. The more experience, someone will more strong in adopting technology.

The hypotheses proposed in this study are:

H1: Performance expectancy has a positive and significant effect on students' behavioral intentions in using e-learning.

H2: Performance expectancy has a positive and significant effect on user behavior through students' behavioral intention to use e-learning.

H3: Hedonic motivation has a positive and significant effect on students' behavioral intentions in using e-learning.

H4: Hedonic motivation has a positive and significant effect on user behavior through the behavioral intentions of students in using e-learning.

H5: Habit has a positive and significant effect on students' behavioral intentions in using e-learning.

H6: Habit has a positive and significant effect on student user behavior in using e-learning.

H7: Habit has a positive and significant effect on user behavior through the behavioral intentions of students in using e-learning.

H8: Behavioral intentions have a positive and significant effect on student use behavior in using e-learning.

METHODS

This study uses a quantitative research design. This study consists of independent variables, those are performance expectancy (X1), hedonic motivation (X2), and habit (X3), and the mediator variable, namely behavioral intention (Z) and the dependent variable, namely use behavior (Y). The sampling technique in this study used proportional random sampling, with this technique hopes all members have the same opportunity to be sampled according to their proportions. The population in this study amounted to 2893 students. The technique of determining the sample size in this study uses the Slovin formula.

The data collection technique in this study used a questionnaire which adopted from research that conducted by Venkatesh,

Table 1. Distributionof The Samples Number in Each Department

No	Department	Distribution of the number sampels
1	Accountancy	83
2	Economic Development	60
3	Economic Education	118
4	Management	90
Total of samples		351

Source: Processed Data (2021)

Table 2. Grid of the Quetionaire Instrument

Variable	Definition	Indicators	No Item
Performance expectancy (X1)	The use of technology will provide consumers and leads on performance (Brown et al., 2016).	Perceived usefulness	PE1
		Job fit	PE2
		relative advantages	PE3
Hedonic motivation (X2)	Pleasure feeling after using technology (Venkatesh, et.al., 2012).	system is fun	HM1
		system is enjoyable	HM2
		system is very entertaining	HM3
Habit (X3)	Activity learned and goal oriented as behavioral response (Tarhini, 2019).	use system has become a habit	H1
		addicted to using system	H2
		must using system	H3
Behavioral Intention (Z)	Probabilitas as individu in doing behavioral (Alshehri, 2019).	use system on future	BI1
		use system on daily life	BI2
		use system frequently	BI3
User Behavior (Y)	The intensity of user in using technology (Venkatesh, et.al., 2012).	usage time	UB1
		usage frequenty,	UB2
		usage variety	UB3

Source: Processed Data (2021)

et. al, (2012). The measurement of each variable in the questionnaire uses a Likert scale. The weighting is done by using option in a way that strongly agrees is given a weight of 5, agrees is given a weight of 4, moderately agrees is given a weight of 3, disagrees is given a weight of 2 and disagrees is given a weight of 1. The grid of research instruments can be seen in the Table 2.

The model that will be used in this research is the causality model. The technique to test the proposed hypothesis is to use Structural Equation Models (SEM) with the help of Warp PLs 6.0.

RESULT AND DISCUSSION

The indicator score with the construct score (loading factor) with the criteria for the loading factor value of each indicator > 0.701 and the p-value < 0.05 so every indicator is declared valid. The model fit test has 3 test indices, namely average path coefficient (APC), average R-squared (ARS) and average variance factor (AVIF) with APC criteria and ARS accepted with p-value < 0.05 and AVIF < 5.

Table 3. Indicators of Loading Factors

Variable	Indikator	Loading Factor	p-value
Performance expectancy (PE)	PE1	0.868	<0.001
	PE2	0.746	<0.001
	PE3	0.885	<0.001
Hedonic motivation (HM)	HM1	0.789	<0.001
	HM2	0.776	<0.001
	HM3	0.724	<0.001
Habit (H)	H1	0.768	<0.001
	H2	0.902	<0.001
	H3	0.890	<0.001
Behavioral Intention (BI)	BI1	0.720	<0.001
	BI2	0.732	<0.001
	BI3	0.834	<0.001
User Behavior (UB)	UB1	0.795	<0.001
	UB2	0.844	<0.001
	UB3	0.795	<0.001

Source: Processed Data (2021)

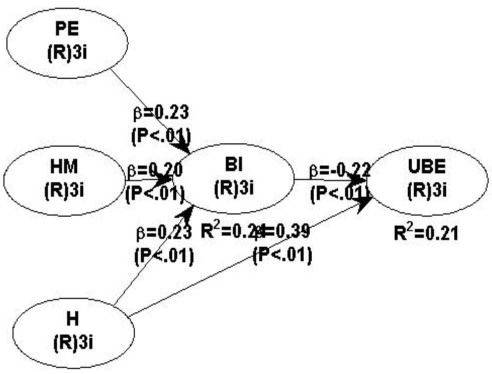

Figure 2. The Results Of The Hypothesis Testing Model
Source: Processed Data (2021)

The test results of the model with the path coefficient can be seen in Figure 2. The loading factor value for each variable can be seen in the Table 5.

Table 4. Model Fit And Quality Indices

Model Fit and Quality Indices	Result	Fit criteria	Representation
Average path coefficient (APC)	0.252	P<0.001	Good
Average R-squared (ARS)	0.225	P<0.001	Good
Average adjusted R-squared (AARS)	0.22	P<0.001	Good
Average block VIF (AVIF)	1.458	acceptable if <= 5, ideally <= 3.3	Ideal
Average full collinearity VIF (AFVIF)	1.689	acceptable if <= 5, ideally <= 3.3	Ideal
Tenenhaus GoF (GoF)	0.347	small >= 0.1, medium >= 0.25, large >= 0.36	Ideal
Sympson's paradox ratio (SPR)	1	acceptable if >= 0.7, ideally = 1	Ideal
R-squared contribution ratio (RSCR)	1	acceptable if >= 0.9, ideally = 1	Ideal
Statistical suppression ratio (SSR)	1	acceptable if >= 0.7	Ideal
Nonlinear bivariate causality direction ratio (NLBCDR)	1	acceptable if >= 0.7	Ideal

Source: Processed Data (2021)

Table 5. Combined Loadings and Cross-Loadings

	PE	HM	H	BI	UBE	Type (a	SE	P value
PE1	0.868	0.017	0.365	-0.015	0.102	Reflect	0.05	<0.001
PE2	0.746	0.017	-0.52	-0.013	-0.21	Reflect	0.05	<0.001
PE3	0.885	-0.03	0.084	0.026	0.075	Reflect	0.05	<0.001
HM1	0.02	0.789	-0.05	0.196	-0.09	Reflect	0.05	<0.001
HM2	0.008	0.776	-0.05	-0.111	0.039	Reflect	0.05	<0.001
HM3	-0.002	0.724	-0.03	-0.225	0.088	Reflect	0.05	<0.001
H1	0.882	0.051	0.768	-0.625	0.43	Reflect	0.05	<0.001
H2	-0.406	0.02	0.902	-0.037	-0.05	Reflect	0.05	<0.001
H3	0.48	-0.02	0.89	-0.01	0.081	Reflect	0.05	<0.001
BI1	-0.046	-0.17	0.412	0.72	-0.06	Reflect	0.05	<0.001
BI2	-0.147	0.084	-0.22	0.732	0.097	Reflect	0.05	<0.001
BI3	0.169	0.077	-0.17	0.834	-0.04	Reflect	0.05	<0.001
UBE1	0.6	0.02	-0.69	-0.391	0.795	Reflect	0.05	<0.001
UBE2	-0.377	-0.01	0.529	0.174	0.844	Reflect	0.05	<0.001
UBE3	-0.332	-0.02	0.114	0.423	0.795	Reflect	0.05	<0.001

Source: Processed Data (2021)

The Effect of Performance Expectancy on Students Behavioral Intentions in Using E-Learning

Performance expectancy is the highly considered aspect in the use of e-learning in this study, because in the concept of performance expectancy it is the concept of the usefulness of a adopted technology. Usability is an important aspect in the concept of performance expectancy. This study proves that performance expectancy has an effect on behavioral intentions. The path coefficient value is 0.226 with p-value <0.001. Performance expectancy contributes to behavior intention in adopting e-learning by 10%. When students believe that e-learning is able to provide benefits and usefulness in learning, learning objectives are achieved, increasing capacity and capability in learning will give students interest and intention in adopting an e-learning platform.

Chau, et al., (2014) explained that the performance expectancy is a concept that similar with the perceived usefulness of TAM, and the usefulness is an important aspect of forming one's intentions and attitudes in adopting technology. Venkatesh, et.al (2012) also stated that performance expectancy is a factor that determines a person interest and intention in using technology. This means that students adopt an e-learning platform, they will consider the benefits and uses. Based on the uses and benefits that will be obtained, students will make a decision between e-learning adopting or choosing anoother alternatives in learning.

The Effect of Hedonic Motivation on Students Behavioral Intentions in Using E-Learning

Hedonic motivation as a pleasure will be obtained by someone in using learning technology. The pleasure and enjoyment of using e-learning has an effect on behavioral intention, because students psychologically will prefer to learn with unique things like the use of e-learning. Hedonic motivation that has been formed in students will lead to the intention to use e-learning. The pleasure will arise when adopting technology will give students different things.

Students who enjoy in using technology will have a positive impact on intentions and interest in using e-learning. Students will have different interests and intentions when compared to students who do not have hedonic motivation in adopting e-learning. This study proves that hedonic motivation has an effect on behavioral intention, the path coefficient value is 0.197 with p-value <0.001. The amount of hedonic motivation contribution to behavioral intention is 6%. Other research explains that hedonic motivation affects interest and intention in adopting technology (Ramirez, et.al, 2019).

The Influence of Habit on The Behavioral Intentions of Students in Using E-Learning

The habit in using technology will have an impact on a strong desire to adopt e-learning. The habit of adopting technology will provide students with an experience when using e-learning. Students who are familiar with technology will not feel worried and stutter about technology. This condition will affect the interest and intention of students in using e-learning. This study states that habit affects the behavioral intentions of students in using e-learning with a path coefficient value of 0.226 with a p-value <0.001. The amount of hedonic motivation contribution to behavioral intention is 10%.

Venkatesh (2012) explains that habit is measured as the extent to which an individual believes that behavior is automatic and that it is a predictor of intention to use technology. Other research stated that habit can predict intention to adopt technology in learning, so it will have a good impact on educational institutions (Kim and Lee, 2020; Nikolopoulou, et.al., 2020; Omar, et.al., 2019; Wong, et.al., 2019). Students who already have the habit and experience in accessing and using technology will give their own interest in adopting e-learning.

The Influence of Habit on Student User Behavior in Using E-Learning

This study states that habit affects student user behavior in using e-learning with a path coefficient value of 0.386 with p-value <0.001. The contribution of the influence of habit on user behavior in adopting e-learning is 16%. Habit factors that arise in adopting technology, students will not think long or will not consider various reasons. Students will form an attitude to act that automatically adopts e-learning. Habit will grow and build a response quickly and automatically to an action.

Students will reflexively adopt e-learning due to habit or experience in adopting technology. Kim and Lee (2020) explain that habit has a positive effect on actual technology use. The formed attitude that from a habit in adopting e-learning is an attitude will continuously be implemented in the long term and continuously. Habit or experience in adopting technology will be applied in using e-learning. Students who already have a habit of adopting technology will try their best to access learning through the e-learning platform.

The Influence of Behavioral Intentions on Student Use Behavior in Using E-Learning

Behavioral intentions is a determining factor for students in using e-learning. it means that a strong interest and intention will have an impact on the consistent of using e-learning. Intention or desire to use e-learning will provide energy and motivation in adopting an e-learning platform. A strong intention will have an effect on student attitudes in using e-learning. It means intention very important as a controller of student attitudes in adopting e-learning. This study found that behavioral intentions affect student user behavior in using e-learning, with a path coefficient value of

0.222 with a p-value <0.001. The contribution of behavioral intentions to user behavior in adopting e-learning is 6%.

Strongly embedded intentions will give user behavior in students when they will adopt e-learning. The factor of students' intention and interest in adopting e-learning will be the main driver in using e-learning. Other studies explained that the intention to use e-learning will have an influence on the regular use of e-learning (Kim and Lee, 2020; Jayanth and Murugan, 2020; Nikolopoulou, 2020).

The Effect of Performance Expectancy on User Behavior Through The Behavioral Intention of Students in Using E-Learning

Performance expectancy has an effect to user behavior in using e-learning through behavior intention, so it will have an impact on continuous individual use. The path coefficient value is 0.050 with a p-value of 0.012. The contribution of the influence of performance expectancy on user behavior through behavioral intentions in adopting e-learning is 13%. Performance expectancy has an effect on user behavior through behavioral intention, which will have a higher effect on students in using e-learning in learning because of internal encouragement, namely the intention will also have an effect on consistent use of technology.

Chao, (2019); Fagan, (2019); Sidik and Syafar, (2020) explained that performance expectancy has a positive effect on behavior intention and will also have an impact on user behavior. So, performance expectancy has an indirect effect on user behavior in using e-learning through behavior intention. Behavioral intention as a mediating variable will have a stronger influence in actual use of e-learning.

Previous research explained that the use of e-learning because of the intention and consistent use is very beneficial for teachers and students (Kim and Lee, 2020; Adov, et.al., 2020; Nikolopoulou, et.al., 2020; Wong, et.al., 2020; Jayanth and Murugan, 2020). Teachers and students will be more consistent in using e-learning because of the performance expectancy factor and the benefits to be gained from technology, this will lead to the intention to use e-learning and have an impact on students' attitudes in actually adopting e-learning.

The Effect of Hedonic Motivation on User Behavior Through The Behavioral Intentions Of Students in Using E-Learning

Pleasure feelings from students in using technology will have a good influence on behavioral intentions and affect user behavior in using e-learning also. This study proves that hedonic motivation affects user behavior indirectly through behavioral intentions in using e-learning. The path coefficient value is 0.044 with a p-value of 0.011. The contribution of hedonic motivation to user behavior through behavioral intentions in adopting e-learning is 11%. Otherwise, hedonic motivation has an indirect effect on user behavior in using e-learning.

Students will be interested and want to use technology because there is a psychological boost, namely a sense of pleasure and enjoyment when using e-learning. High intention will have an effect on student attitudes to use e-learning as a habit in learning. Other research, explains that when someone perceives and feels the use of technology in learning as fun, it will have an effect on the use of technology in a high intensity (Omar, et.al., 2019; Wong, et.al., 2019; Al-Zoubi and Ali, 2019; and Chao, 2019).

This study proves that henonic motivation is an aspect of forming student attitudes in adopting e-learning. Students will consider using e-learning based on the value of pleasure or enjoyment obtained. Venkatesh, et.al. (2012) stated that people do not only care about performance, but also the feelings obtained from using a technology and found that hedonic motivation is a factor that influences behavioral intentions towards technology adoption.

The Influence of Habit on User Behavior Through The Behavioral Intentions of Students in Using E-Learning

Habit factors that affect toward user behavior will be stronger if it is through behavioral intentions. This study proves that habit affects user behavior through behavioral intentions. The path coefficient value is 0.050 with a p-value of 0.013. The contribution of the influence of habit on user behavior through behavioral intentions in adopting e-learning is 14%. Habit has an indirect effect on user behavior. The habit of adopting technology will give you a strong interest and intention in using e-learning, because habit is something that is subconscious and tends to become a kind of need, so it is difficult to change. Students will understand the benefits and drawbacks when adopting an e-learning platform.

Habit in using technology will provide experience and will be a strong consideration, when students want to adopt technology. Students will be interested in adopting e-learning because they already know the advantages and are able to operate the e-learning platform well. Habit in adopting technology will give birth to intention and interest in adopting e-learning and trying to use e-learning continuously, thus will affect the actual use of e-learning. Wong, et.al. (2019) explained that habit has an influence on behavioral intentions and will also affect user behavior.

CONCLUSION

The results of this study conclude that performance expectancy, hedonic motivation, and habit have a direct effect on student behavioral intentions in using e-learning. Habit and behavioral intentions also have a direct effect on student user behavior in using e-learning. Performance expectancy, hedonic motivation and habit affect user behavior through students' behavioral intention to use e-learning.

The UTAUT 2 modeling in this study was able to describe the behavior of students in adopting e-learning during the Covid 19 pandemic. In this study, habit was the construct that contributed the most in explaining student behavior in adopting e-learning when compared to the performance expectancy and hedonic motivation factors. In the other studies, performance expectancy and hedonic motivation are determining factors and make a major contribution to UTAUT 2 modeling.

Recommendation for the further research development in the context of UTAUT 2 modeling, researchers can research which related to the price value variable or financial use that will be issued by students in adopting learning technology. This is based on the learning activities on technology so it requires finance to access the technology.

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