Intention to Adopt E-Learning with Anxiety: UTAUT Model

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ABSTRACT

This study aims to analyze the Intention model to adopt e-Learning in students with anxiety levels using computers. This study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) model to examine several variables that affect the Intention to adopt e-learning in students with high levels of boredom on the computer. Several variables were used to predict. Intentions are performance expectation (PE), effort expectation (EE), Attitude towards use (ATU), and social influence. This study used 250 student respondents in South Sumatra and Yogyakarta, Indonesia. Each respondent is described as having a high level of boredom in using the computer. The analytical tool used is structural equation modeling (SEM), namely PLS-SEM. The results show that UTAUT can explain the Intention to adopt e-learning among students with general anxiety. The results of this study also show that performance expectations (PE), effort expectations (EE), and attitudes towards the use (ATU) of e-learning have a significant effect on the Intention to adopt e-learning. Social influence has no significant effect on behavioral Intention. UTAUT can be used as a feasible integrated theoretical framework, adequately designed and implemented in studies using SEM-PLS statistical analysis. UTAUT is very helpful as a future framework in designing and promoting the adoption and use of e-learning technologies among students.

Keywords: PE; EE; anxiety; Attitude; social influence; Intention.

1. INTRODUCTION

Learning and teaching technology have shown significant acceptance under the COVID-19 pandemic. E-learning technology allows students and teachers to conduct remote learning on an unprecedented scale. Both lecturers and students feel the

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condition of social restrictions. Universities should rethink using available technology resources to provide higher education services and benefit from those services (Ayuni & Mulyana, 2019). This sudden change has put unprecedented pressure on Internet infrastructure and e-learning platforms (Favale et al., 2020); (Sugandini et al., 2022). Students are more aware of the uses and advantages of e-learning (Al-Fraihat et al., 2020). However, e-learning can cause tremendous difficulties for students and lecturers. Students often become isolated and alienated because of their reluctance to participate in online communities. The online community can stem from several factors, such as personality, sense of transactional distance in the online environment, lack of trust and confidence in participants in the online community, lack of nonverbal communication, connection difficulties, poor writing skills, and language barriers (Rasheed et al., 2019). For lecturers, preparing online courses is much more time-consuming than preparing for face-to-face learning in class (Guri-Rosenblit, 2018). E-Learning is considered a future educational paradigm as an alternative to higher education standards developed for future generation Z (Dhawan, 2020). However, current e-learning developments are imperfect, and many scholars question the readiness for future massive adoption of e-learning in higher education (Rapanta et al., 2020; Scherer et al., 2021). The shift in education to e-learning has caused tremendous difficulties for universities and has sparked comprehensive research discussions. Students' mental health vulnerabilities in e-learning environments and complex stresses were also revealed in online learning during the COVID-19 outbreak (Ayuni & Mulyana, 2019). According to Li et al. (2021), the prevalence of depression and anxiety for college students worldwide was 39% and 36%, respectively, during the COVID-19 pandemic. Thus, the effect of anxiety on e-learning adoption cannot be ignored. Technology anxiety, according to (Troisi et al., 2022), is a barrier to technology acceptance that can be a significant predictor or determinant of behavioral Intention. Technology anxiety is defined as a user's emotional state, such as nervousness, uncertainty, and fear related to learning to use technology. This concern arises because technology has negative consequences, such as losing important data or making mistakes. Anxiety can lead to technology rejection and technophobia, adverse emotional reactions to technology, and technostress (Daruwala, 2020); (Troisi et al., 2022).

Technology anxiety is a negative affective state towards technology that produces negative emotions (Davis, 1989). Low technology skills, trust in using technology, privacy, cost, technology dependence, and organizations that adopt technology are the causes of technology resistance or anxiety. On the other hand, technology anxiety can also negatively affect scores, privacy risks, and learning costs, and both are determinant factors that contribute negatively to the Attitude toward technology adoption (Ghasemaghaei, 2020). Because e-learning is a new technology for students, the learning process may be a perceived obstacle for them to adopt it. For students, perceived negative values will increase technology anxiety, and students assume that their previous knowledge is insufficient to adopt the application quickly. In addition, the perception of learning costs not only occurs before adoption but can also remain after (Hu et al., 2022).

This study continuously analyzes the Intention to use e-learning in students with high anxiety levels. The basic theory used is the Unified Theory of Acceptance and Use of Technology (UTAUT) model. This research is necessary because it can provide novelty related to the influence of anxiety as a control variable that affects the

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Intention to adopt e-learning. This research is expected to cover the shortcomings of previous research that has not involved the anxiety factor in the success of e-learning adoption. In addition, universities in new normal conditions after the Covid-19 pandemic also need information related to the sustainability of e-learning for their institutions. Previous research conducted by (Hu et al., 2022); (Abdous, 2019) and (Inan et al., 2022) show that anxiety can cause failure in e-learning adoption even though e-learning adoption is forced to be adopted as a form of learning during the Covid-19 pandemic. This study uses anxiety as an individual internal variable that e-learning users feel, but this variable is not included in the research model. Anxiety is used as a control variable. The goal is to choose users with a high level of anxiety so that this study can justify the Intention to adopt e-learning for users already saturated with e-learning. Thus, the results of this study can be used by universities to make policies for modifying hybrid learning. Hybrid learning is learning that practices online and face-to-face methods together. Researchers choose students who have a high level of saturation because researchers want to justify whether the Intention to adopt e-learning can be predicted by performance expectations (PE), social influence (SI), effort expectancy (EE), and attitudes towards the use (ATU). Previous research has analyzed chiefly these factors in the user's assumed good emotional state.

2. LITERATURE REVIEW

2.1. UTAUT and Intention to adopt

The basic concept underlying UTAUT is the Intention to use information technology. The Intention is a direct predictor of actual technology use. Behavioral intentions are conceptualized as technology acceptance (Venkatesh et al., 2003). Intention to adopt e-learning is defined as a person's Intention to adopt and use e-learning technology in the future (Al-Mamary, 2022); Sugandini et al., (2022). UTAUT states that there are four main determinants of technology acceptance and use, namely: 1) The expected benefits that individuals will receive from using technology (Performance Expectancy), 2) the expected ease of use of technology (Effort Expectancy), 3) a significant perception of others to believe that technology should be used (Social Influence) and 4) expected technical support when using technology (Facilitation Conditions). Other moderating control factors were: age, gender, experience, and voluntary use (Venkatesh et al., 2003). The UTAUT model was initially developed and formulated in a workplace context (Venkatesh et al., 2003), but some have successfully applied UTAUT to the field of digitalization of education (Wijaya et al., 2022); (Al-Mamary, 2022); and (Shaqrah & Almars, 2022).

2.2. Attitudes towards the use of e-learning

Attitudes toward the use are the level of a person's positive or negative feelings about the target behavior (Davis, 1989). Attitude describes a positive or negative disposition toward a person, object, or situation. Attitude is an individual characteristic that describes positive or negative behavior and is a reflection of feelings and knowledge about a particular object (Grimaldo & Uy, 2020). Previous research has found a significant relationship between attitudes and intentions to use technology (Wijaya et al., 2022). Users tend to develop their behavior based on the dispositions set on a technology (Andrews et al., 2021). Another finding shows that Attitude is a significant

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predictor of students' Intention to use E-learning and plays an essential role in student learning in the classroom. Hussein (2017) asserts that students' attitudes toward computers influence the Intention and perception of using e-learning.

H1: Attitudes towards the use of e-learning affect the Intention to use e-learning

2.3. Effort expectancy (EE)

Effort expectancy is the level of ease associated with the use of technology. Effort expectancy is another essential variable that builds behavioral intentions toward technology (Al-Mamary, 2022). Effort expectancy determines the ease of connecting with technology (Venkatesh et al., 2003). Venkatesh, Thong, & Xu (2016) show that the relationship between Effort expectancy and behavioral Intention is often found to be significant and positive. Meanwhile (Khechine et al., 2020) found an insignificant relationship between Effort expectancy and behavioral intentions. Ain et al. (2016) showed a non-significant relationship between Effort expectancy and behavioral intentions in the context of learning management systems and new technologies. (Wijaya et al., 2022) conducted a study to analyze the behavioral Intention of mathematics teachers in using micro-lectures in mathematics in China. The Unified Theory of Acceptance and Use of Technology (UTAUT) model is used as the design model. The results of his research show that Performance Expectancy, Effort Expectancy, and Social influence affect behavioral Intention.

H2: Effort expectancy affects Intention to use e-learning

2.4. Performance expectations (PE)

Performance expectancy is the extent to which individuals believe that using the system will help to achieve gains in performance (Venkatesh et al., 2003). UTAUT, introduced by Venkatesh (2003), is a model that predicts user intention to use e-learning. UTAUT proposes two significant factors that influence behavioral Intention to use: performance expectations and effort expectations. Performance expectations are similar to perceived usefulness in TAM and refer to users' perceptions of how much information technology helps in their work. Effort expectations are the opposite of perceived ease of use in TAM, i.e., user-perceived effort to use information technology. Venkatesh et al. (2003) argue that performance and business expectations significantly influence users' behavioral Intention of users to use information technology. (Inan et al., 2022) conducted a study to test the adoption of IoT applications for educational purposes focusing on student perspectives at Taibah University Malaysia. The results showed that social support facilitated conditions, innovativeness, and effort expectancy substantially affected the acceptance and use of the respective IOET applications.

Meanwhile, performance expectations and perceived usefulness have the weakest effect on IoT adoption. Aqlan et al. (2021) show the results of a study on the effect of performance expectations on Intention to use technology. The study results state that Performance Expectancy determines a person's Attitude toward using this information system. The same report shows that performance expectations have a substantial and beneficial impact on someone who adopts behavioral goals and utilizes IT systems (Al-

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Mamary, 2022). Other similar studies have concluded that performance expectations will change their perception of adopting learning management systems.

H3: Performance expectations affect the Intention to use e-learning

2.5. Social influence

Social influence is the level of importance felt by individuals over the trust of others for them to use new technology (Venkatesh et al., 2003). Social influence consists of subjective norms, social factors, and image. Awang Kader et al. (2022) found that social influence did not affect technostress. In addition, most respondents admitted that other people or friends did not influence the decision to use online learning because it was mandatory during the COVID-19 outbreak. Furthermore, most respondents agreed that social influence did not influence their decision to use online learning as it has become mandatory to use the platform for learning and teaching during the COVID-19 lockdown. Haron et al. (2021) revealed a correlation between social influence and technostress and affected the Intention to adopt online learning.

H4: Social influence affects the Intention to use e-learning.

3. RESEARCH METHOD

3.1. Research participants

The research was conducted by distributing survey questionnaires to Yogyakarta students and South Sumatra Indonesia using Google Forms. A total of 250 were obtained for further analysis.

3.2. Instrument development.

The questionnaire used in this study consisted of two parts. Section 1 focuses on gathering the basic demographics of the respondents, including (1) gender, (2) age, and (3) education. Section 2 discusses five research variables: performance expectations, effort expectations, social influence, attitudes to computers, and behavioral intentions to use continuously. Respondents were asked to rate the strength of their identification with questionnaire items on a 5-point Likert-type scale, from 1 (strongly disagree) to 5 (strongly agree). Table 1 shows the questionnaire items and their references.

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Tabel 1. Research variables and questionnaire items.

Variables	Questionnaire items	References
Attitude to the computer (ATT)	ATT1: I believe that using a computer is a good idea. ATT2: I believe that using a computer is recommended ATU3: I am satisfied with using the computer.	(Hu et al., 2022)
Effort Expectancy (EE)	EE1: Using the e-learning app is easy EE2: The user interface and application function menu are easy to use EE3: Using e-learning apps to learn is easy.	(Huang & Chueh, 2022): (Akinnuwesi et al., 2022)
Performance Expectancy (PE)	PE1: Using the app is very helpful for studying PE2: Using the app can improve my skills PE3: Using the app allows me to learn quickly	(Huang & Chueh, 2022): (Akinnuwesi et al., 2022)
Social Influence (SI)	SI1: My lecturer encourages me to use the app to study SI2: My classmate uses the app to study. SI3: A lot of learning people will use apps to do it.	(Huang & Chueh, 2022):
Behavior intention (BI)	BI1: I am willing to continue using the app to study BI2: I will continue to use e-learning in the future BI3: I intend to continue using e-learning in the future, at least as actively as today	(Huang & Chueh, 2022); (Hu et al., 2022)
Anxiety	AN1: Feeling Nervous, anxious, or restless AN2: Unable to stop or control worry	(Hu et al., 2022)

3.3. Measures

This study uses Smart-PLS with a Structural Equation Model (SEM) approach to test the hypothesis. This approach is often used in social science studies because of its accuracy in analyzing psychometric models. According to Kim & Lee (2020) and (Wijaya et al., 2022), Smart-PLS is used for the following reasons: (1) hypothesis testing can be performed if the distribution is not normal; (2) it can be used with less than three items, and (3) can be used regardless of sample size. The PLS-SEM step

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consists of reflective measurement and structural model assessment. The assessment of the reflective measurement model revealed the loading of reflective indicators, the reliability of internal consistency consisting of Cronbach's alpha and composite reliability, convergent validity through Average Variance Extracted, and discriminant validity using the Heterotrait-Monotrait Ratio (HTMT).

Meanwhile, statistical assessments such as VIF values, path coefficients, t-statistics, and p-values were used to evaluate the structural model. The t-test was used to assess the significance of the relationship between variables. The reliability of the questionnaire structure uses the Cronbach value of each variable to verify the internal consistency between the questionnaire items.

Table 2. Results of loading factor, validity, and reliability

Latent Variable	Indicator	Loading	t-Value	Composite Reliability	Cronbach's Alpha	AVE
Performance Expectancy (PE)	PE1	0.869	20.826	0.904	0.842	0.759
	PE2	0.862	25.117			
	PE3	0.883	26.598			
Effort Expectancy (EE)	EE1	0.803	17.937	0.879	0.794	0.708
	EE2	0.859	22.014			
	EE3	0.860	24.879			
Social Influence (SI)	SI1	0.897	19.254	0.916	0.863	0.785
	SI2	0.900	25.279			
	SI3	0.859	24.742			
Attitude to the computer (ATT)	ATT1	0.878	28.398	0.914	0.859	0.780
	ATT2	0.888	24.247			
	ATT3	0.884	25.256			
Behavior intention (BI)	BI1	0.876	22.224	0.870	0.775	0.690
	BI2	0.812	21.361			
	BI3	0.803	20.221			

Table 2 shows the loading factor for each variable in the range of 0.803 to 0.900, which is a good value. Each variable shows a value that is almost evenly distributed and consistent (Hair et al., 2006); (Hair et al., 2014). Table 2 also contains information about the measurement model, such as factor loading, t-value, internal consistency, Cronbach's alpha, and AVE (Average Variance Extracted).

The convergent validity of the measurement model is shown by observing: (1) item reliability; (2) composite reliability; and (3) Average Variance Extracted (AVE). For the reliability of the items using Cronbach's alpha value. Table 2 shows that all constructs of Cronbach's alpha value are more significant than the threshold of 0.70. Each construct in Table 2 has composite reliability greater than 0.5, indicating good internal consistency reliability among latent variables. Furthermore, to analyze the variance, the AVE of all constructs has a value greater than 0.5, indicating that these items meet the criteria of convergent validity. A high AVE indicates that the measurement process in the developed model is of high quality and can explain the model.

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Table 3. Results of discriminant validity based on Fornell–Larcker criterion results

	Attitude to computer	Behavior intention	Effort Expectancy	Performance Expectancy	Social Influence
Attitude to computer	0.883				
Behavior intention	0.820	0.831			
Effort Expectancy	0.787	0.725	0.841		
Performance Expectancy	0.773	0.760	0.710	0.871	
Social Influence	0.697	0.666	0.786	0.707	0.886

The discriminant validity analysis in this study uses the Fornell-Larcker criteria, which uses the square root of the AVE for each latent variable and the correlation coefficient between other variables. In Table 3, the Fornell-Larcker criteria for discriminant validity are presented by showing the correlation matrix between items (diagonal elements represent the square root of the AVE). The observed diagonal element is greater than the other correlation values between other latent variables, thus fulfilling the discriminant validity requirements. However, several studies have shown that using the Fornell-Larcker criteria is not sufficient for discriminant validity analysis. To determine discriminant validity, the HTMT ratio is required. According to Naveed et al. (2020) and Teo et al., (2008), the maximum threshold value for HTMT is 0.9. Table 4 shows the HTMT statistics that support discriminant validity.

Table 4. Additional validity discriminant measurement results based on HTMT.

	Attitude to computer	Behavior intention	Effort Expectancy	Performance Expectancy	Social Influence
Attitude to computer	0.805				
Behavior intention	0.847	0.816			
Effort Expectancy	0.808	0.837	0.861		
Performance Expectancy	0.810	0.813	0.855		
Social Influence				0.828	

4. RESULTS

4.1. Description of respondents and variables

This research is quantitative research that uses student respondents. The number of samples used is 250 students who live in Yogyakarta and North Sumatra. This study aims to examine the behavioral intention model on e-learning adoption with a high

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level of anxiety. Questionnaires were distributed to respondents who had anxiety levels in e-learning learning and spent a time ranging from 10 to 20 minutes filling out the questionnaire. Table 5 shows the data of research respondents, and table 6 describes each research variable.

Table 5. Descriptive statistics of respondents

Items	Type	Frequency	Percentage
Gender	Male	142	56.6%
	Female	108	43.4%
Age	18–20	52	20.6 %
	21–22	100	40.0%
	23–25	48	19.2%
	26-up	50	20.2%
Education	Bachelor's	156	62.6 %
	Master's	94	37.4%

Table 6. Descriptive statistics of variable

Variable name	Mean	Description
Anxiety	4.34	Feeling Nervous, anxious, or on edge
	4.38	Not being able to stop or control worrying
Performance Expectancy (PE)	4.28	Have high-performance expectations
Effort Expectancy (EE)	4.28	A high ease of use
Social Influence (SI)	4.09	The influence of others is strong
Attitude to the computer (AC)	4.01	Attitude on the computer is good
Behavior intention (BI)	4.36	Intention to use high

4.2. Evaluating the Structural Model and Hypothesis Testing

The evaluation of the structural model in Figure 1 shows the hypothetical relationship between the proposed variables. The basic model uses the UTAUT theory, which is carried out to determine the Intention to adopt e-learning in anxiety conditions.

Figure 1 shows a structural model based on which has 15 items. The results of the structural model analysis are shown in table 7. The suitability of the model generated from Smart-PLS 3 shows acceptable suitability. Its R^2 value indicates this. According to Venkatesh et al. (2003) and Alghazi et al. (2021), if the R^2 value greater than 0.67 is considered high, the variance between 0.33 to 0.67 is considered moderate, while between 0.19 and 0. 33 is considered weak. The proposed model accounts for 71.9% of the variance in Intention to use e-learning. Standardized Root Means Square Residual (SRMR) was used to assess the suitability of the PLS model. A good fit is defined by an SRMR value of less than 0.10 (Hu & Bentler, 1998). The SRMR value in the study was 0.065. Hu & Bentler (1998) show that the model meets the model fit criteria if the RMS Theta or Root Mean Square Theta value is < 0.102 and the NFI value is > 0.9. The results of this study indicate that the Theta value is 0.021, and the NFI is 0.910. So it shows a very suitable model. The model has reliability and validity and can explain

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the hypothesized relationship according to the measured R^2. Table 7 shows information about the direct effect on each relationship between variables.

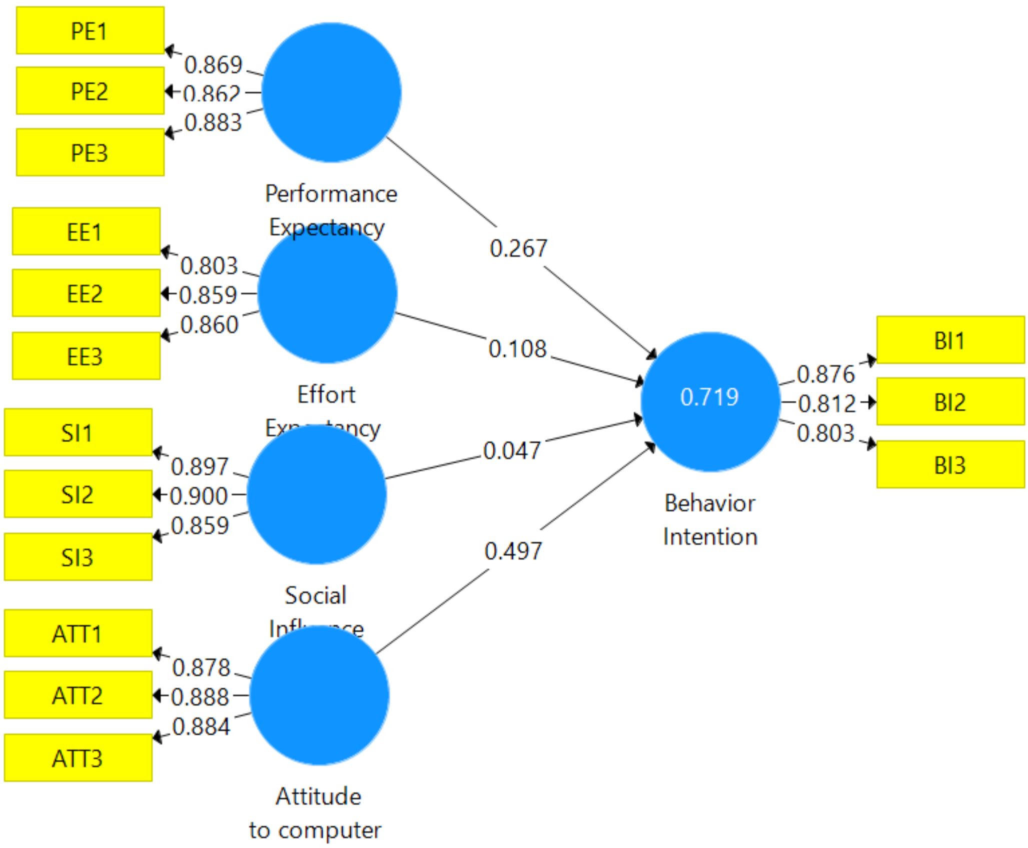

Figure 1. The conceptual framework model.

Table 7. Hypothesis testing of factors affecting the use of e-learning

Relationship	Path Coefficient	Sample Mean	Standard Deviation	t Statistic	p Values	Decision of Hypothesis
Attitude to the computer → Behavior Intention	0.497	0.492	0.072	6.919	0.000	Significant
Effort Expectancy → Behavior Intention	0.108	0.110	0.064	2.693	0.041	Significant
Performance Expectancy → Behavior Intention	0.267	0.270	0.062	4.332	0.000	Significant
Social Influence → Behavior Intention	0.047	0.046	0.062	0.746	0.456	Not Significant

Table 7 shows the path coefficient values, the standard deviation of the sample mean, t-statistics, and the significance level (p-value). Because not all paths have t-statistics greater than 1.96 and p-values less than 0.05, not all paths show significant results. The results of this study indicate that Attitude to the computer, effort expectancy, and performance expectancy significantly positively affects behavioral Intention

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(supporting Hypothesis 1,2,3). Social Influence does not have a significant positive effect on behavioral Intention (does not support Hypothesis 4).

5. DISCUSSION AND IMPLICATION

The research focuses on behavior intention in using e-learning with anxiety conditions in users. This study identifies factors in the UTAUT model that can affect behavior intention in using e-learning. The results of this study are broadly consistent with the results of other studies on the acceptance of e-learning technology. There is only one path that is not significant, namely social influence. The results of this study indicate that the effect of performance expectancy on BI is a significant positive. The result shows that although students are at a high level of anxiety due to the obligation to use e-learning, students' perceptions of the ability of e-learning to help to learn become good. The results of this study are consistent with the research findings of Venkatesh et al. (2003); (Al-Mamary, 2022) and Wijaya et al. (2022). The results of the second research show a significant effect of effort expectancy on behavior intention. Students consider that overall, e-learning is easy to use and does not require significant effort to apply. The influence of EE on BI is relatively low, around 10.8%. This means that students during the two years of the pandemic and using online learning felt that they were used to this application, so they had not experienced many failures in running it.
The results of this study support (Al-Mamary, 2022); (Venkatesh et al., 2003); (Khechine et al., 2020) and (Wijaya et al., 2022). Social influence does not have a significant relationship with BI. This is because e-learning is a condition of necessity or involuntariness. So the presence or absence of the influence of others has no impact on the Intention to use because users are forced to use this application (Venkatesh et al., 2003). So that other people's influence in using e-learning becomes useless or insignificant. Students will continue to use e-learning even though the social influence is not supportive, and vice versa. The results showed that in anxiety conditions, it turned out that a good attitude towards computers had the most significant influence in forming intentions to use e-learning. A love for computers can overcome boredom due to using e-learning applications for too long. The results of this study are consistent with those of Wijaya et al. (2022), Andrews et al. (2021), and Hussein (2017). They confirmed that good intentions and attitudes in computer applications have a significant relationship.

6. CONCLUSIONS AND LIMITATION

6.1. Conclusions

The primary purpose of this study is to examine behavior intention in a structural model influenced by Attitude to computers, PE, EE, and social influence. The results of model testing indicate that the fit model is met, which means that the model can explain the various variables used and has good validity and reliability. Three variables influence behavior intention: PE, EE, and Attitude to the computer, and one variable, social influence, is not significant in influencing behavior intention.

6.2. Limitations and Future Research

In this study, the sample was limited to students with a high level of anxiety. However, the proposed research model has not analyzed the moderating effect of this anxiety. So

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the researcher cannot justify further related the moderating effect of anxiety on each relationship between the observed variables. This study also did not analyze the moderating effect of experience. The results of a survey conducted by researchers show that the experience of using e-learning is one of the factors that cause students to reduce anxiety in using e-learning. Another limitation of this study is that the researcher did not use negative statements in the questionnaire, which might lead to inconsistencies in respondents' answers.

Further research recommends using other methods such as interviews and observation to ensure more specific and convincing results. In future research, it is necessary to conduct further research on no significant social influence on behavior intention, and the influence of social influence needs to be studied further.

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