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Examining the Effect of Teacher's Age Difference on Learning Technology Adoption Using Technology Acceptance Model

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Abstract. Online learning has become a habit in the era of the COVID-19 pandemic. However, changes in technology-based learning methods, especially learning using Microsoft 365, are still not accepted by all teachers. Teachers' acceptance of technology is related to one of the social demography variables of the teachers, that is age. The age gap is one of the causes of differences in teacher acceptance of technology. Therefore, this study aims to determine the technology acceptance of the teachers aged 18-35 years and aged 36 years and over. The authors collected the data through online questionnaires with a sample size of 75 teachers. Technology acceptance from both groups of teachers in Surabaya was made with a theoretical framework using the Technology Acceptance Model (TAM). The intention to use (IU) of learning technology is predicted with exogenous variables, namely perceived usefulness (PU), perceived ease of use (PEU), perceived risk (PR), and social influence (SI). The result is TAM model formed for the younger group of teachers (18-35 years) was different from the group of older teachers (36 years and over). In the young age group, the perceived risk variable did not affect the teacher's intention to use technology, contrary for teachers aged 36 years and over. It shows that the young teachers tend not to feel difficulties using technology than the older teachers.

Keywords: technology acceptance, learning technology, online learning, covid-19, age difference, education

INTRODUCTION

Technology in education is growing, including in the pandemic era. The use of technology for learning becomes a dependency during the pandemic because of social distancing policies [1]. Therefore, the government to change the learning method to online learning. One technology that is widely used is media conferencing. More than that, teachers also need media to deliver subject matter, give assignments, and evaluate the learning outcomes of students. This triggered one of the existing policies in the city of Surabaya, namely the implementation of Microsoft 365 in learning in schools.

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Teacher acceptance of technology is crucial during online learning. However, there is a gap in the ability of teachers to use technology [2]. The diversity of teacher acceptance of technology can cause problems during online learning. Differences in age range and education level cause gaps in the ability to use technology. Teachers' acceptance of technology also considered the social background of the school. Beliefs teachers who teach in socially difficulties schools are less sure about the digital technology benefits [3]. In addition, not all students have online learning infrastructures, such as computers or mobile phones, and internet access. So, it becomes another obstacle in the learning process. Although, it cannot deny that online learning still happens during pandemic covid-19 conditions.

The technology acceptance model (TAM) is widely used to determine the factors that influence technology acceptance. The TAM explained technology acceptance well based on combining meta-analysis in structural equation modeling to explain teacher adoption of digital technology [4]. The model of an extended TAM with facilitating conditions explains sports science education students' use of e-learning [5]. The perceived usefulness and perceived ease of use have a direct positive influence on teachers' adoption of ICT [6]. Incorporating perceived risk to construct TAM can increase the validity of predictive models [7] in technology adoption. An extended version of TAM with the social influence has significantly influenced technology acceptance [8]. The conclusion of [9] is perceived usefulness does not affect intention to use technology directly because teachers adopt technology mainly because of the obligation aspect as social influence.

In this study, the authors aim to examine teachers' adoption of learning technology using TAM with the consideration age difference. The authors use four latent variables, namely perceived usefulness (PU), perceived ease of use (PEU), perceived risk (PR), and social influence (SI), used to predict the intention to use (IU) technology. Besides that, the authors also examine the PU variable as mediating variable between PEU and IU variables.

LITERATURE REVIEW

Covid-19 has had an impact in various fields, including education in Indonesia. Learning is carried out remotely to avoid the transmission of the covid-19 virus. The face-to-face learning system has changed to online learning because the learning process must continue [10]. The implementation of the distance learning policy has resulted in the application of online learning using online learning technologies [11], such as learning management systems, online classrooms, and video conferencing. This makes teachers and staff inevitably adapt to online learning technology [1]. Not all teachers in the school immediately accepted this change easily. The gap in technology mastery due to socio-demographic factors of teachers [2] and school social background has an impact on technology acceptance [3]. Limited access to infrastructures, such as computers and internet access, exists during online learning [2] due to the diversity of school and student conditions. Various studies on online learning during the pandemic have been carried out.

Technology Acceptance Model (TAM) is one model to determine the factors that influence the acceptance of new technology. TAM was introduced by [12] to predict individual technology adoption using two factors or variables, that is perceived usefulness and perceived ease of use. Perceived usefulness and perceived ease of use of technology affect a person's intention to use technology [12, 13]. Technology that is useful and easy to use for users will encourage them. Both constructs, perceived usefulness and perceived ease of use, are hypothesized positive relationship to use technology. In addition, the conceptual model of TAM shows a causal relationship between perceived usefulness and perceived ease of use. Perceived ease of use of technology affects perceived usefulness so that perceived usefulness mediates the relationship between perceived ease of use and intention to use. Extended TAM by adding perceived of risk show a negative relationship with intention to use technology [8]. The addition of a perceived risk variable enriches technology adoption research and can increase predictive validity [7]. Another study concluded that perceived risk, technology type, user experience, and sex variables, as moderating variables significantly affect user technology adoption [14]. Acceptance of technology is also affected by social influence, involving subjective norms, volunteerism, and image [8].

Structural Equation Modeling (SEM) was used to test TAM. SEM applies the concepts in confirmatory factor analysis, path analysis, and regression analysis. SEM is a multivariate analysis method that can be used to describe the relationship between observational variables (indicators) and variables that cannot be measured directly (latent variables) [15]. Latent variables or constructs are divided into endogenous and exogenous variables. The manifest variables (indicators) can be observed directly from the measurement data in the study [16]. Structural Equation Modeling (SEM) consists of structural and measurement models [17]. There are two approaches in SEM to estimate the parameters, namely the covariance-based SEM (CB-SEM) and variance-based SEM (VB-SEM) [15]. The ability of VBSEM (or called PLS-SEM) can attract researchers to use PLS-SEM, such as to predict from complex models, require flexible data, and access to the software [16].

METHODOLOGY

Data was collected using an online survey using Google Forms. The sample of this study was teachers in Surabaya who filled out online questionnaires. The sampling method is quota sampling. The sample size is 75, each of which is 34 teachers aged 18-35 years and 41 teachers aged over 35 years. The collected data is constructed into a conceptual model using the Technology Acceptance Model. The model was used to study the phenomenon of teacher acceptance of new technology, especially in online learning to use Microsoft 365. The conceptual model consists of five latent variables, namely intention to use (IU), perceived usefulness (PU), perceived ease of use (PEU), social influence (SI), and perceived risk (PR). The IU, an endogenous variable, is predicted with four other latent variables (as exogenous variables). Besides that, the PU was hypothesized as mediating variable between PEU and IU variables. The manifest variables, or indicators, measured each latent variable with a Likert scale of 1-5. Each PU, PEU, PR, SI, and IU variable measured with 5, 5, 5, 4, and 2 indicators, respectively. In this study, data analysis uses the variance-based SEM or VB-SEM method, referred to PLS-SEM method, using SmartPLS 3 software.

RESULT AND DISCUSSION

The characteristics of the samples used in this study, most of the teachers surveyed were female (70.67%), over 35 years (54.67%), and bachelor (86.67%), like in Table 1. It shows the conditions that usually occur in schools as educational institutions. Therefore, the demographics of this sample can adequately represent the population. Most of them are new to technology (Microsoft 365) during online learning and rarely use it.

TABLE 1. Demography of the Samples

Variables	Frequency (Percent)
Sex	
• Male	22 (29.33 %)
• Female	53 (70.67 %)
Age	
• 18-35 years	34 (45.33 %)
• Over 35 years	41 (54.67 %)
Education	
• 3-year Diploma	3 (4.00 %)
• Bachelor	65 (86.67 %)
• Master	7 (9.33 %)

The purpose of this study was to determine the variables that affect technology acceptance from two different groups, namely the group of teachers aged 18-35 years and over 35 years. Table 2 shows the sample characteristics for the two groups, which is the same pattern as Table 1. Most of the respondents are female and have bachelor's degrees. For the age group above 35 years, the data does not show teachers with diploma education.

TABLE 2. Samples of Teachers Aged 18-35 years and Over 35 years

Variables	Frequency (Percent)	
	Aged 18-35 years	Over 35 years
Sex		
• Male	13 (38.24 %)	9 (21.95 %)
• Female	21 (61.76 %)	32 (78.05 %)
Education		
• 3-year Diploma	3 (8.82 %)	0 (0.00 %)
• Bachelor	28 (82.35 %)	37 (90.24 %)
• Master	3 (8.82 %)	4 (9.76 %)

Conceptual Model

The initial conceptual model Figure 1 was used to predict the intention to use (IU) variable. The hypothesis in this conceptual model will confirm whether each of the exogenous variables (PU, PEU, PR, and SI variables) affects the IU variable (endogenous variable). The PU variable is also a mediating variable between PEU and IU. There are five manifest variables to measure the PU, PEU, and PR variables, respectively, four manifest variables to measure SI variable, and two manifest variables to measure IU variable. The hypotheses of the conceptual model are as follows.

H1: Perceived ease of use technology influence significantly intention to use technology

H2: Perceived ease of use technology influence significantly perceived usefulness of technology

H3: Perceived usefulness of technology influence significantly intention to use technology

H4: The social influence on the technology has a significant effect on the intention to use technology

H5: Perceived risk on the technology has a significant effect on the intention to use technology

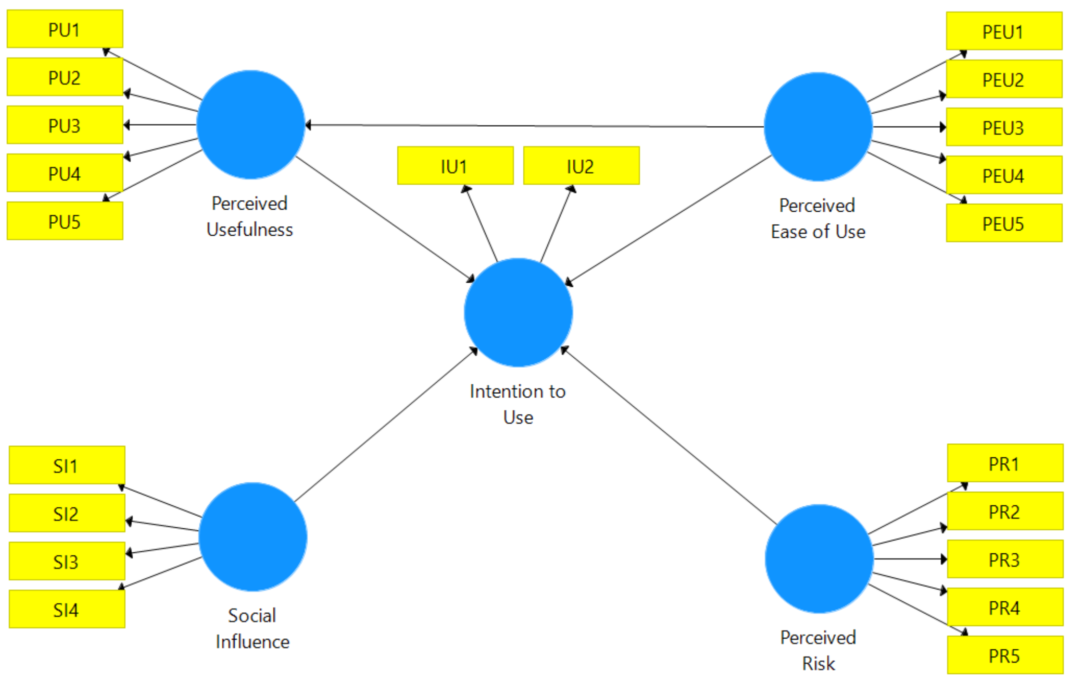


FIGURE 1. Initial Conceptual Model

Model Estimation

Model estimation is done to get the coefficient values of the latent variables using bootstrap. The coefficient values show the relationship between exogenous variables and endogenous variables. Table 3 and Table 4 show the estimates of final models (in Figure 2), PEU and SI variables have a positive relationship with IU, while PR has a negative relationship with IU at the 0.05 level of significance α. This is following the existing theory (H1 and H4). The easier the teacher's acceptance of technology, the greater the teacher's desire to use the technology. Social influence turned out to have a significant influence on the use of technology, namely Microsoft 365 by teachers in schools. This shows that social conditions play a role in the success of the policies implemented by the government during the pandemic in particular. However, the assumption of a large risk will be inversely proportional to teacher acceptance of learning technology, especially for teachers aged over 35 years. The PU variable has a different relationship in the two groups. The PU variable has a negative correlation with IU for teachers aged 18-35 years, while the PU variable has a positive correlation with the IU variable for teachers aged over 35 years. However, in theory, the greater the benefits that will be obtained from the use of technology, the desire to use the technology will increase so that the estimated value (loading factor) is positive. The negative estimated value could be because there are indicators used to measure the PU variable that has not been included in the model. In addition, this allows for other relationships between constructs, such as mediating variables, moderating variables, or confounding variables, which are not yet present in the conceptual model. So, the sign of the coefficient is not under the theory.

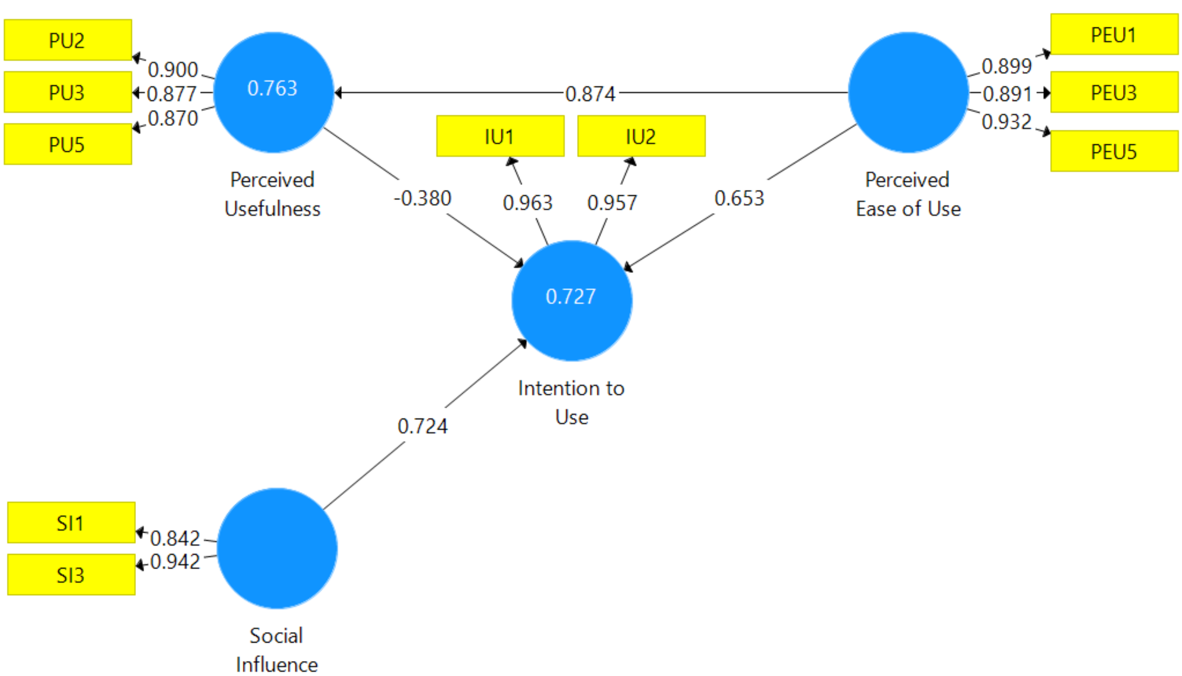
TABLE 3. Path Coefficient and Indirect Effect of Teachers Aged 18-35 years Group

Path	Estimate	T Statistics	P-Value
PU → IU	-0.380	1.991	0.047
PEU → IU	0.653	4.280	0.000
PEU → PU	0.874	18.521	0.000
SI → IU	0.724	7.231	0.000
PEU → PU → IU	-0.332	2.177	0.030

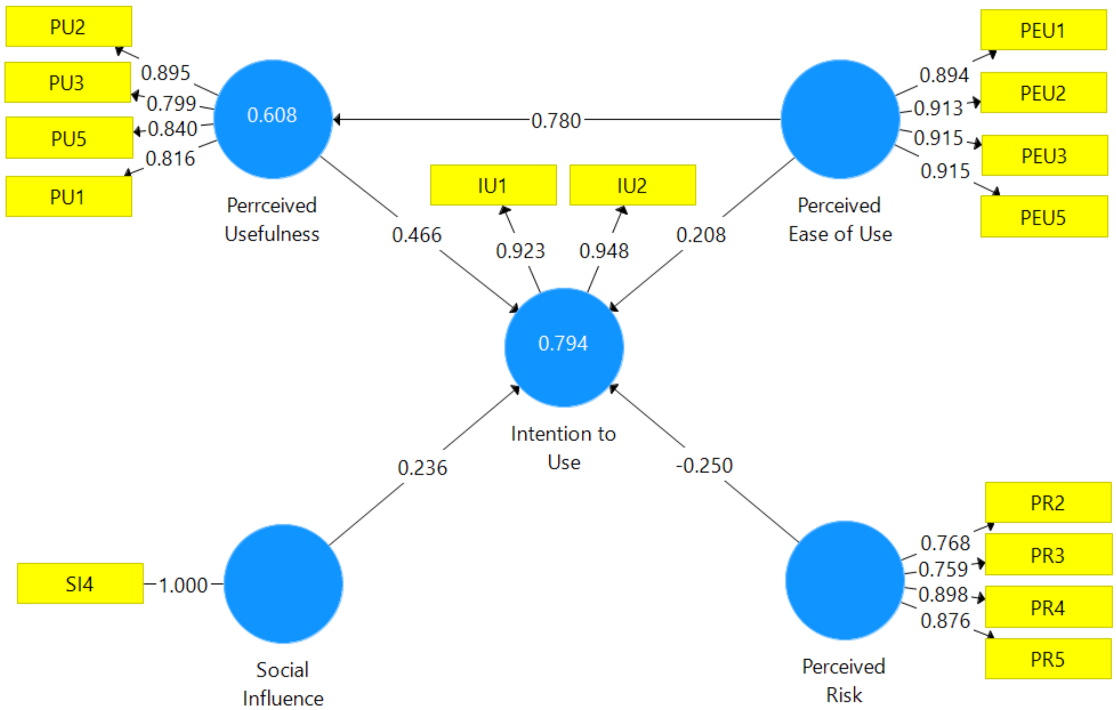
TABLE 4. Path Coefficient and Indirect Effect of Teachers Aged Above 35 years Group

Path	Estimate	T Statistics	P-Value
PU → IU	0.466	3.828	0.000
PEU → IU	0.208	2.136	0.033
PEU → PU	0.780	10.255	0.000
PR → IU	-0.250	2.648	0.008
SI → IU	0.236	2.626	0.009
PEU → PU → IU	0.363	3.606	0.000

The final model of the two shows different results. Figure 2 perform that the PU, PEU, and SI variables affect the intention to use Microsoft 365 of teachers aged 18-35 years, while four exogenous variables influence the intention to use Microsoft 365 of teachers over 35 years. This implies that there are differences in learning technology adoption, particularly the use of Microsoft 365 for different groups of teachers. The results show that the respondents aged 18-35 years are not worried about these risks in using Microsoft 365. The PR variable influences intention to use Microsoft 365 of teachers aged 18-35 years, while the younger age group (18-35 years) is not. The PR variable was measured significantly with four manifest variables (indicators), namely the PR2, PR3, PR4, and PR5 indicators. On the other hand, the PU variable provides a mediating effect between the PEU and IU variables (PEU → PU → IU). The IU variable is directly and indirectly influenced by the PEU variable. However, the two estimates of the mediating variable have different relationships. This could be due to problems in the relationship between PU and IU (Table 3)



(a) Teachers Aged 18-34 years



(b) Teachers Aged Over 35 years

FIGURE 2. Final Model

Validity and Reliability Test

Both models were tested for validity to determine whether the model is valid to measure the next analysis. The reliability test tested whether the instrument could measure the question items consistently. Based on Table 5, all indicators in the model in Figure 2 are valid because the value of T is more than the value of the t distribution with 74 degrees of freedom and a significance level of 0.05 (α), which is 1.99. In addition, we can compare the P-value with α. It is found that all of P values are less than 0.05 so the model is valid for subsequent analysis. All Cronbach's Alpha values of more than 0.7 meet the criteria to declare that the model is reliable.

TABLE 5. Results of Validity and Reliability Test

Latent Variables	**Indicators**	**Outer Loading (P-Value)**		**Cronbach's Alpha**	
		Age 18-35	**Age Above 35**	**Age 18-35**	**Age Above 35**
IU	IU1	0.963 (0.000)	0.923 (0.000)	0.915	0.859
	IU2	0.957 (0.000)	0.948 (0.000)		
PEU	PEU1	0.899 (0.000)	0.894 (0.000)	0.893	0.930
	PEU2	-	0.913 (0.000)		
	PEU3	0.891 (0.000)	0.915 (0.000)		
	PEU5	0.932 (0.000)	0.915 (0.000)		
PU	PU1	-	0.816 (0.000)	0.858	0.847
	PU2	0.900 (0.000)	0.895 (0.000)		
	PU3	0.877 (0.000)	0.799 (0.000)		
	PU5	0.870 (0.000)	0.840 (0.000)		
SI	SI1	0.842 (0.000)	-	0.758	0.859
	SI3	0.942 (0.000)	-		
	SI4	-	1.000		
PR	PR2	-	0.768 (0.000)		1.000
	PR3	-	0.759 (0.000)		
	PR4	-	0.898 (0.000)		
	PR5	-	0.876 (0.000)		

Collinearity and R-Squared

Collinearity test determines whether there is a linear relationship between variables. Based on the VIF values of each variable, there are no variables that have more than 5. It shows that there are no cases of multicollinearity for both groups. Final model of younger teacher group performs R-Squared and R-Squared Adjusted more than 0.7 for IU (*R-Squared* = 0.727, *R-Squared Adjusted* = 0.700) and PU variables (*R-Squared* = 0.763, *R-Squared Adjusted* = 0.756). For older teacher group performs R-Squared and R-Squared Adjusted more than 0.7 for IU (*R-Squared* = 0.794, *R-Squared Adjusted* = 0.771), but PU variable has lower than 0.7 (that is *R-Squared* = 0.608 and *R-Squared Adjusted* = 0.598).

CONCLUSION

The result is TAM model formed for the younger group of teachers (18-35 years) was different from the group of older teachers (36 years and over). In the young age group, the perceived risk variable did not affect the teacher's intention to use technology, contrary for teachers aged over 35 years. It shows that the young teachers tend not to feel difficulties in using technology than the older teachers. Next study, mediating variable, moderating variable, or confounding variable can be used to improve the result of that conceptual model.

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