The Key Determinants of Social Media Use in Teaching during the Covid-19 Outbreak: Indonesia Case

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Abstract

This study aims to provide empirical evidence on how higher education institutions (HEIs) teacher educators use SM in teaching during the Corona Virus Disease (Covid-19) outbreak. Evaluation of the factors that are the key to implementing the use of SM in education during the Covid-19 outbreak is essential. We used a survey aiming to answer the research questions of the study. The study participants are 297 faculty members from all over the Indonesian faculty of education and teacher training. The findings of the study reported that all hypotheses are significant. Facilitating Condition (FC) significantly predicts Perceived Ease of Use (PEU) and Perceived Usefulness (PU). Similarly, PEU is positively related to PU and Intention to Use (IU). PU also significantly determines IU. In addition, IU is significantly correlated with Actual Use (AU). The highest path coefficient is achieved by the relationship between the FC and PU. PEU and PU are the lowest relationship. Suggestions and recommendations are offered for the betterment of teaching and learning processes during the Covid-19 outbreak.

Keywords
Reliability, social media, teaching, validity

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Introduction

While Covid -19 caused many communities to quit and stay at home for some time, schools and colleges have entered into uncharted territory. During this period, it is important to make teacher educators continue the teaching and learning process. Fortunately, some evidence-supported strategies can help support teaching activities to keep educational activities going. One way is to utilize Social Media (SM) in the teaching and learning process in schools and universities. SM has been popular. Research on SM potential for higher education is important, especially in situations where educational institutions such as schools and colleges are temporarily closed (Chick et al., 2020). Particular concerns have been paid to the use of tools like Instagram, WhatsApp, YouTube, Facebook, and Twitter. Several studies have reported positive impacts of SM use in higher education that guide to a good relationship between old generations and new generations (Karvounidis, Chimos, Bersimis, & Douligeris, 2014).

The attitude and the use of SM emphasize the ambivalent results on these tools' benefits and challenges in higher education. Besides, the improving role of SM in academic staff's professional trainings, including lecturers, is also being continuously researched. The way SM technology changes work patterns in the academic world has also been widely discussed. However, apart from the claims of the advantages of using SM in education, it is still questionable whether and why the lecturers use or not the technology in their teaching and other professional activities. If they use SM, what factors influence the integration of SM.

In this context, an article was written by (Manca & Ranieri, 2016), whose research was abruptly in Italy became the reference for this research. In their investigation, Manca and Ranieri, (2016) reported the lack of use of SM in professional teaching work. The lecturers' technophobic attitude from their research can be used as one of the reasons why lecturers do not use SM in research. This reluctance was not merely because of technophobic attitudes but also the beliefs of the lecturers as a trigger for the lack of use of SM by university lecturers. Besides that, the attitude they have about teaching and learning also determines the lecturers to innovate in teaching is still a big question, especially during distance learning. The lack of research on the use of SM in developing countries with the subject of teaching staff is the finding of previous researchers. Therefore, this study was conducted aiming to elaborate on factors that affect the use of SM in teaching during distance learning due to Covid-19 pandemics.

Literature Review

Covid-19 (Corona Virus Disease-19)

Armed conflicts, forced displacement, disasters caused by climate change, and other crises have caused disruption the education of children and young people across the world. The number is increasing in a way that is unprecedented with the emergence of Covid-19. Education was hit extremely hard by the Covid-19 outbreak, with more than 1.54 billion students dropping out across the countries, affecting 87.6% of the world's enrolled students. Dropout rates worldwide are likely to increase due to this major disruption to access to Education (Caplan, Clements, Chadwick, Kadirgamar, Morgan, & Rao 2020). While other critical needs are being addressed, the need for education cannot be overlooked, and this has the same detrimental impact if left unresolved. In the time of the Covid-19 global pandemic, the disruption of education can have prolonged implications. A risk of regression emerges significantly for children whose basic learning (reading, math, and language) is not strong. The millions of students were deprived of their right to education, especially girls, are more prone than boys to health and well-being risks during Covid-19. These are the children and youth should be prioritizes in education. Therefore, solutions are sought for distance learning that involves blended learning, including the use of SM (Mahaffey, 2020).

Use of total personal and professional SM

One of the most highlighting phenomena in the history of digital technology was when a global survey reported an increase in the use of SM applications among adults, particularly in the USA and in Europe. SM tools are depicted as driving Internet utilization, as more and more people create and share their content via SM platforms. The use of SM applications is also influencing current academic practice, including general or specific social networking sites (Facebook or ResearchGate), sharing applications (YouTube), and content creation services (Blogs or Wikis) (Halic, Lee, Paulus, & Spence, 2010). Traditional dimensions have expanded to include integration in teaching practices.

This implies that education practitioners enable sharing with the public and opportunities for application and evaluation by others. From this perspective, SM can facilitate public to provide general and special public social demands (Chick et al., 2020; Hall, 2014). However, adoption rates for educational purposes lag behind compared to personal utilization. Facebook has been informed to be the most seen SM site for personal use more than half of higher education lecturers visit at least every month (Kirschner & Karpinski, 2010; Kross et al., 2013; Steinfield, Ellison, & Lampe, 2008). The usage of Facebook expands the daily, weekly and monthly usage of compared to other SM for personal use.

Challenges the use of SM in the activities of teaching

Pleanty of studies have been conducted and informed the positive impact of SM in higher Education level (Deandrea, Ellison, Larose, Steinfield, & Fiore, 2012; Gikas & Grant, 2013; Kirschner & Karpinski, 2010). However, the disadvantages of using SM were also informed by other researchers (Hew & Cheung, 2010; Selwyn, 2009). Indeed when considering practice-based teaching regarding the integration of SM applications, university lecturers must face some problems related to their prior experiences with technology, their expectations, and their pedagogy, beliefs and practices (Ajjan & Hartshorne, 2008; Kimmons & Veletsianos, 2014). Ajjan and Hartshorne (2008), for example, reported that most of the respondents had a good attitude on the adoption of SM as a instructional tool.

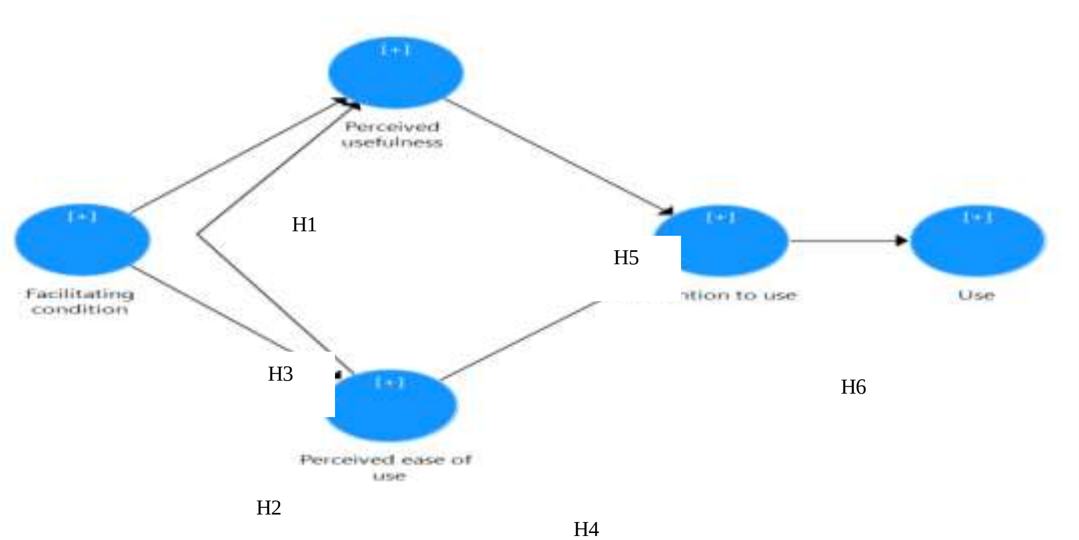
Framework and hypothesis

TAM is one of the most significant new versions Ajzen and Fishbein's TRA or theory of action research in the source of literature. TAM is the most widely used model of technology use and acceptance (Venkatesh, Morris, Davis, & Davis, 2003). TAM was developed by Davis et al. (1985) replacing many of TRA's measures—ease of use and usefulness. TRA and TAM refer to the situation when someone delivers an intention to act. They will be having no limited activities (Davis, Bagozzi, & Warshaw, 1989).

In this study, TAM's main variables, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) were included to be hypothesized to predict Intention to Use (IU). In addition, the Facilitating Condition (FC) is added as an external variable (Figure 1). PU has been evaluated to be useful in teaching, namely to foster students' achievement, improve information and knowledge sharing, provide good facilitation to learn and improve teachers' productivity and creativity (Montero Perez, Peters, & Desmet, 2014; Zacharis, 2012). Plenty of studies have reported about the role of PEU in technology integration (Ma & Liu, 2004; Schepers & Wetzels, 2007). If technology was perceived to be easy to use, the PU would improve and produce more comprehensive IU technology (Liaw & Huang, 2003; Saeed & Abdinnour-Helm, 2008; Teo, Lee, & Chai, 2008). FCs could be supported by addressing appropriate infrastructure, professional improvement, technical support, and policies supporting technology integration in education (Koh, Chai, & Tsai, 2010).

Hypothesis 1: FC will significantly affect PU
Hypothesis 2: FC will positively influence PEU
Hypothesis 3: PEU will positively influence PU
Hypothesis 4: PEU will positively affect IU
Hypothesis 5: PU will be significant in predicting IU
Hypothesis 6: IU will be positive in affecting Actual Use (AU)

Figure 1. *Conceptual model*



Methodology

The study of technology integration and pedagogical innovation in higher education is a very complex process. We used a survey aiming to answer the research questions of the study. Creswell (2014) states that the survey design is a design study that differs from experimental research. They do not involve the care given to the participants by the researcher. Because survey researchers do not experimentally manipulate conditions, they cannot explain cause and effect as well as experimental researchers can.

Participants

An online survey with Google form was distributed to three universities, school of education in two Indonesian provinces, Jambi and Yogyakarta. The explanation of SM technology was included within the factors Influencing SM use during pandemics distance learning. The respondents involved in this study are 297 members. Ninety-three of them are males, and 204 of the participants are females. Two hundred and seventy-seven of the participants have five years or more teaching experience, while 93 faculty members have experience of fewer than five years.

Instruments

For the current research, the items were adapted from related previous studies. The items were in relation to TAM and SM integration in education. The questionnaire was utilized to create the information in regard to the five factors informed in the proposed model (Fig. 1) in the context of SM integration during distance learning. The factors of PU, PEU, IU, and AU were adapted from the original TAM framework (Davis, 1985) and other previous studies (Mukminin, Habibi, Muhaimin, & Prasojo, 2020; Prasojo, Habibi, Mukminin, Sofyan, Indrayana, Anwar., 2020). The five-factor questionnaire included 13 items, a 5-point Likert scale from strongly agree (5) to strongly disagree (1). The survey instrument is divided in double sections. Section A is demographic information, where the respondents are asked to give information in relation to their gender, age, and teaching experience. The second section was the measurement items. SmartPLS3.0 software was used to elaborate the hypotheses through the use of procedures of a Partial Least Squares Structural Equation Modeling (PLS-SEM).

Data Analysis

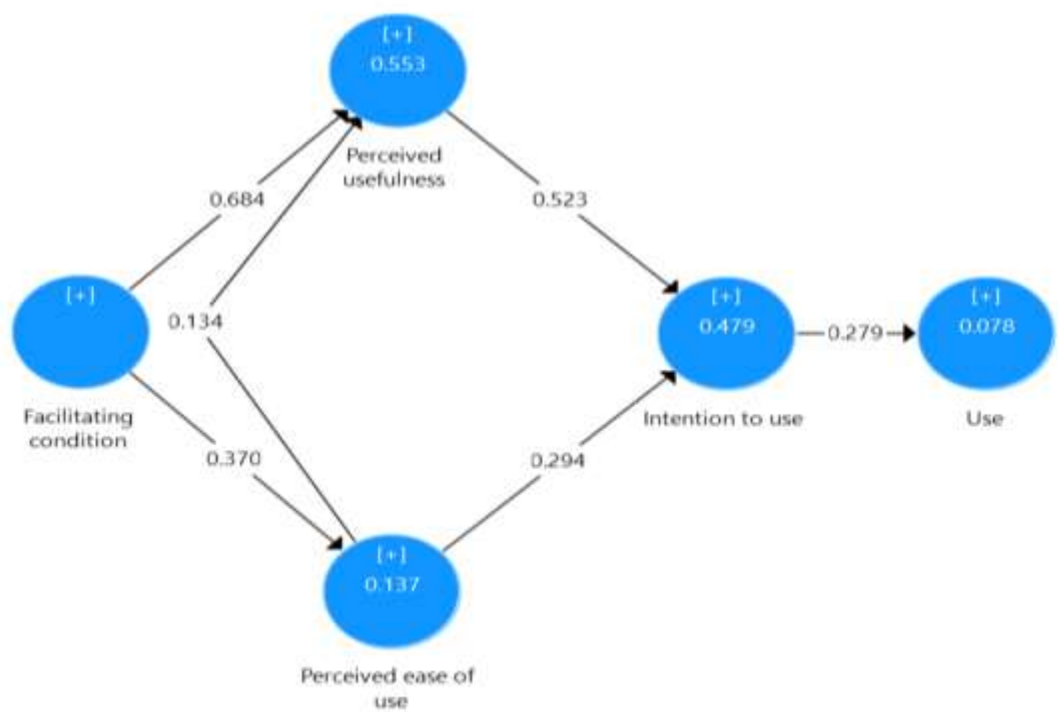
Data analysis was done within two steps of assessment; measurement models and structural models (Habibi, Yusop, & Razak, 2020b, 2020a; Hair, Matthews, Matthews, & Sarstedt, 2017). For the measurement mode, the researchers used SmartPLS 3 and assessed indicator loading, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2019). The descriptive report was evaluated. The structural model was reported through coefficient path value, t- value, and p-value (Hair et al., 2019).

Findings

Measurement model and descriptive statistics

Two systematic approaches, namely measurement and structural modeling, were implemented to analyze data (Habibi et al., 2020b; Hair et al., 2020). PLS-SEM was chosen because it can be used to refine models and create complex models to accurately predict the relationship between variables. Reliability and validity of variable measurements were tested through reports of four measurement approaches, namely reflective indicator loading, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2016). The loading of reflective indicators is suggested to be higher than .700 (Hair et al., 2016). Table 1 provides the complete final result of the reflective indicator load. To achieve the final result, one indicator (PU3 and FC3), which obtained a loading value lower than .708, was removed (Hair et al., 2020). The data show that all indicators after deletion exceed the recommended limit values; the data loading values range from .876 to .944.

Figure 2. *Measurement model*



Internal consistency reliability is used to evaluate the consistency of results between indicators. We report Cronbach's alpha values and Composite Reliability (CR). Alpha and CR values are measured in the range 0 to 1. Values should be above .700 and below .950, as suggested by Hair et al. (2020). Table 1 provides the complete results of the alpha and CR values. The values of most of the variables have good internal consistency reliability, exceeding the value offered above .700 and below the value of .95. For CR, the lowest score was for FC (α = .889), and the highest was for PU (α = .940). For the Cronbach's alpha value, FC gets the lowest score (CR = .750) and PU achieves the highest score (CR = .871). Descriptive results computed through the measurement model evaluation in the PLS-SEM are also satisfactory with Mean ranging from 4.046 to 4.537. The complete results of this research measurement model can be seen in Table 4.1.

Table 1. *Measurement model*

		Load	**α**	**rho**	**CR**	**AVE**	**M**	**SD**	**Kurt.**	**Skew.**
FC	FC1 "I will have the resources necessary to teach with the SM technologies during pandemics distance learning"	.899	.750	.751	.889	.800	4.058	.834	-.54	-.486
	FC2 "Training for using SM technologies in teaching will be available for me during pandemics distance learning"	.890					4.046	.759	.176	-.521
IU	IU1 "I will use SM technologies in my future teaching during pandemics distance learning"	.891	.858	.859	.914	.779	4.414	.696	1.491	-1.13
	IU2 "I plan to use SM technologies often in my future teaching during pandemics distance learning"	.881					4.322	.751	.79	-.978
	IU3 "I intend to use SM technologies as much as possible in my future teaching during pandemics distance learning"	.876					4.435	.734	2.379	-1.408
PEU	PEUO1 "Learning to use SM technologies in teaching will be easy during pandemics distance learning"	.886	.882	.882	.927	.809	4.368	.706	3.085	-1.282
	PEUO2 "Using SM	.918					4.53	.671	5.25	-1.822

	technologies in teaching will be clear and understandable during pandemics distance learning"						7		6	
	PEUO3 "Using SM technologies in teaching will be flexible to interact with during pandemics distance learning"	.894					4.455	.705	3.699	-1.53
PU	PU1 "Using SM technologies will improve my teaching performance during pandemics distance learning"	.939	.871	.872	.940	.886	4.266	.749	.846	-.91
	PU2 "SM technologies will enhance my teaching effectiveness during pandemics distance learning"	.944					4.231	.732	.473	-.731
Use	USE1 "I use SM technologies during pandemics distance learning"	1.000	1.000	1.000	1.000	1.000	3.831	1.034	.262	-.806

Convergent and discriminant validity

Average Variance Extraction (AVE) values should be deciphered for convergent validity. Each construction must have a value> .500 or higher, which explains 50% or more of the variance of each indicator. In this study report, the AVE values of all constructs exceed .500 (Sukendro, Habibi, Khaeruddin, Indrayana, Syahruddin, Makadada, & Hakim, 2020). IU has the lowest value of AVE (.779), while PU archives the largest portion of AVE (.886). The data is shown in Table 1.

Discriminant validity problems arise if HTMT is higher than .900 (Habibi et al., 2020a). HTMT above .900 carries out limited discriminant validity (Hair et al., 2020). Informed in Table 2, all HTMT is below .900 or different from 1, establishing the discriminant validity between variables. After the measurement model process, it is calculated for the structural model assessment. Apart from using HTMT evaluation, discriminant validity can also be checked by understanding cross-loading data. If an indicator of the loading value of a construct is higher than the loading value of other constructs, then there is no cross-loading problem (Hair et al., 2016). Table 3 informs that there are no problems related to cross-loading in this study. We report that the outer loading for all constructions (bold) is higher than the cross-loading. In addition to HTMT and cross-loading reports, Fornell Larcker's criteria are calculated in SmartPLS. The distributed variance for constructs should be lower than that of their AVE (Fornell & Larcker, 1981). In view of Table 4, 2 value AVE of all construction is higher than variance with them. Of the three evaluations of HTMT, cross-loading, and Fornell Larcker criteria, the discriminant validity of the study is reported.

Table 2. *HTMT*

	FC	IU	PEU	PU
FC				
IU	.860			
PEU	.455	.570		
PU	.817	.736	.441	
Use	.402	.301	.267	.305

Table 3. *Cross loading*

	FC	IU	PEU	PU	Use
FC1	**.899**	.619	.305	.685	.280
FC2	**.890**	.616	.358	.626	.343
IU1	.593	**.891**	.451	.531	.257
IU2	.613	**.881**	.409	.571	.228
IU3	.622	**.876**	.455	.583	.253
PEOU1	.339	.437	**.886**	.332	.264
PEOU2	.310	.468	**.918**	.341	.209
PEOU3	.348	.435	**.894**	.370	.202
PU1	.674	.591	.341	**.939**	.253
PU2	.706	.607	.387	**.944**	.283
USE1	.348	.279	.250	.285	**1.000**

Table 4. *Fornell-larcker*

	FC	IU	PEU	PU	Use
FC	.895				
IU	.690	.883			
PEU	.370	.497	.899		
PU	.733	.637	.387	.941	
Use	.348	.279	.250	.285	1.000

Assessment of the structural model

Before reporting data for the structural model assessment, the collinearity of each predictive relationship was analyzed. The Variance Inflation Factor (VIF) evaluates that the value must be below 3. Multiple regression calculations were carried out to determine the VIF value (Kock, 2015; Lowry & Gaskin, 2014). All VIF values were reported to be lower than 3 or at a satisfactory level.

Table 5. *VIF value*

	FC	IU	PEU	PU	Use
FC			1.000	1.158	
IU					1.000
PEU		1.176		1.158	
PU		1.176			

Path coefficients of all structural model hypotheses are reported. We run the data through a bootstrap step with 5,000 subsamples. The results show the path coefficients, t-values, and p-values, as well as the statements of significance for all hypotheses, h1-h6. Assuming a significance of 5%, all hypotheses are reported to have a significant relationship and the other one is revealed to be insignificant. The complete results of the coefficient test can be seen in figure 1 and table 6. FCs significantly predicts PEU and PU. Similarly, PEU is positively related to PU and IU. PU also significantly determines IU. Finally, IU is significantly correlated with AU. The highest path coefficient is achieved by the relationship between FC and PU. Meanwhile, PEU and PU are the lowest relationship.

Table 6. *The relationship between variable hypotheses*

H	Path	β	Mean	STDEV	t value	p values	Significance
H1	FC -> PU	.684	.683	.033	2.722	.000	Yes
H2	FC -> PEU	.370	.378	.059	6.309	.000	Yes
H3	PEU -> PU	.134	.135	.033	4.066	.000	Yes
H4	PEU -> IU	.294	.299	.050	5.915	.000	Yes
H5	PU -> IU	.523	.518	.043	12.285	.000	Yes
H6	IU -> Use	.279	.279	.043	6.452	.000	Yes

Coefficient of determination (R^2) and predictive relevance (Q^2)

R-square value (R^2) shows the value of variance elaborated by the exogenous construct. On the other hand, the structural model quality is reported through predictive relevance (Q^2), that is utilized to address an examination process of the predictive relevance for the structural (Streukens, Wetzels, Daryanto, & de Ruyter, 2010). The display of the values was shown in Table 7. R^2 values varied ranging from 0 to 1, a higher value has an indication of a higher level of predictive accuracy. The R^2 value of .75 is considered substantial, while .50 is moderate, and .25 is weak (Hair, Sarstedt, & Ringle, 2019). Table 7 performs the R^2 values; IU (.479, moderate), PEU (.137, weak), PU (.553, moderate), and use (0,078, weak). It can be described that the results are a good level of predictive accuracy.

Further, the model's predictive relevance through the stone-geisser's Q^2 value was done. When the model informs predictive relevance, the accuracy in predicting the data points of model's items is very important (Prasojo, Habibi, Wibawa, Hadisaputra, Mukminin, Muhaimin, &Yaakob, 2020). In this study model, a Q^2 value higher than 0 have an indication that the model's predictive relevance is obtained (.02 as small; .15 as medium .35 as large). The procedure for Q^2 reports was conducted through blindfolding steps. Results for Q^2 are elaborated in Table 7. The results provide the predictive relevance of the study.

Table 7. *R^2 and Q^2*

	R Square	R Square Adjusted	SSE	Q^2 (=1-SSE/SSO)
IU	.479	.477	943.613	.367
PEU	.137	.135	1328.393	.109
PU	.553	.552	512.564	.484
Use	.078	.076	46.727	.073

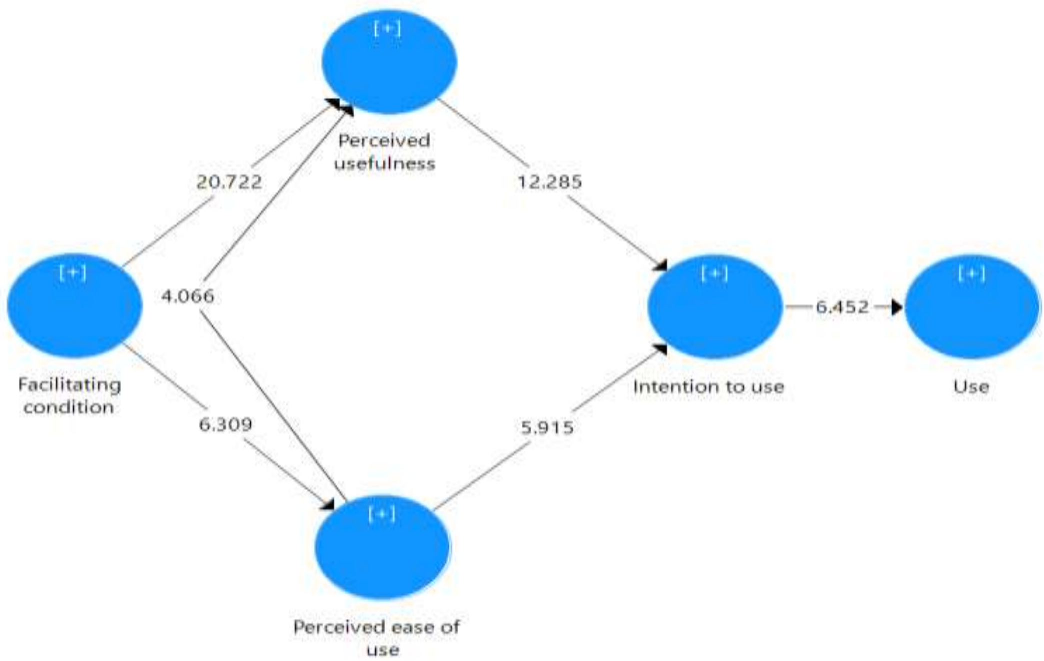
Effect size

Effect size (f^2) aims to evaluate the change in the R^2 when a special factor is eliminated from the model. The cut-off values of effect size: .02 (small effect), .15 (medium effect), and .35 (large effects). The computation findings of the f^2 are informed in Table 5. Concerning Table 8, the effect size of H1 and H2: FC - > PEU (.158, medium & .903, large). The effect sizes for H3 and H4 are (.141, medium & .035, small). PU has a large effect size to IU (.477). Finally, the f^2 of IU is .084 (small). In sum, the research's model results informed that all factors qualify for measurement and structural model; thus, the model is valid and reliable, demonstrating a good level of validity (Nakagawa & Cuthill, 2007; Ruppert, 2004).

Table 8. *F^2*

	IU	PEU	PU	Use
FC		.158	.903	
IU				.084
PEU	.141		.035	
PU	.447			

Figure 3. *Final result*



Discussion

There is a growing development of literature on SM use for various purposes in higher education to support the learning process, student support and engagement, scholarly communication, and build communication and connections (Al-Aufi & Fulton, 2015; Manca, 2020; Sheer & Rice, 2017; Sobaih, Moustafa, Ghandforoush, & Khan, 2016). However, studies were focusing on SM integration during distance education is still limited. Therefore, this study aims to provide empirical evidence on how higher education institutions (HEIs) teacher educators use SM in teaching during Covid-19 outbreak. In exploring factors influencing the use of SM, the TAM framework included in this research has been successful in explaining the process of the adoption of SM during Covid-19 perceived by Indonesian teacher educators. The survey instrument validation would be considered to address a significant contribution to the improvement of structural equation research. The data analysis informed valid and reliable scale. Similarly, previous studies also used a similar method in validating their scales (Muhaimin et al., 2019; Mukminin et al., 2020; Prasojo et al., 2020).

The main goal of this study was to examine factors influencing Indonesian faculty members' IU and use of SM during pandemics distance learning. The main framework applied in this study was TAM (Mugo, Njagi, Chemwei, & Motanya, 2017), supported by the FC as an extended variable. The results informed that the model is an adequate fit. All exogenous constructs have significant positive influences on all endogenous constructs. The significant predicting power of FC to PU and PEU is informed within the results of this study. These reports are similar to what Koh, Chai, & Tsai, (2010) reported that FCs was a significant predictor of PU. The supporting condition like proper infrastructure, professional improvement, technical support, and policies supporting technology can strongly influence Indonesian teacher educators' perceived benefits and ease to use SM in their teaching. Similarly, PEU is also a significant predictor for PU and IU. Further, PU also significantly determines IU. Similar TAM results indicate the importance of perceived benefits and ease to improve users' willingness to use certain technologies in teaching and learning (Ma & Liu, 2004; Montero Perez et al., 2014; Schepers & Wetzels, 2007; Zacharis, 2012). Finally, IU is significantly correlated with AU, proving that when teacher educators have a good level of intention to use SM in their teaching (Sukendro et al., 2020).

Conclusion

Exploration has been widely applied to explore the use of SM. This large study is evidence that SM in learning has been applied in various countries. Nevertheless, only a few studies have done an investigation on the use of media in a pandemic, such as Covid-19. Thus, the current research addresses enrichment to the literature on the comprehension of the current conditions of distance learning during pandemic school closures, an important guide to academics who are interested in conducting similar types of studies. At present, because of school closures, technology acceptance and use have been more complicated and not been able to be avoided than normal conditions. Thus, it is important to maximize investment for long-distance purchases at higher education. An evaluation of the influencing factors of technology use during an outbreak, such as Covid-19, must be applied to a variety of contexts and settings. Besides, this research aims to understand the aspect of access where not all teaching staff have sufficient technological resources related to the conditions of facilitation, particularly internet access. The findings of these studies require support from future academics who have interests in conducting similar research. Stakeholders must have proper preparation for better distance learning that occurs because of the outbreak. Despite the availability of statistical support, this study has several limited resources. Respondents included withi this study were only from teacher educators; more different background respondents should be recommended for further studies. Another interesting suggestion for further research is to comprehend the use of SM from a qualitative approach through interviews. A comparative analysis is also suggested and recommended.

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