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Research article

Using an extended Technology Acceptance Model to understand students' use of e-learning during Covid-19: Indonesian sport science education context

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A R T I C L E I N F O

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A B S T R A C T

This study was to explore factors predicting the use of e-learning during Corona Virus Disease 2019 (Covid-19) among sport science education students In Indonesia Higher Education Institutions (HEIs). The study was conducted through survey with 974 participating students from five Indonesian HEIs. An extended Technology Acceptance Model (TAM) with facilitating condition as the external factor was implemented to be the theoretical framework of this study. An analysis method through Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to measure and assess the proposed model. The findings informed that: (1) the TAM-based proposed scale has been successfully explained factors predicting the use of e-learning among Indonesian sport science students during the pandemic; (2) the finding of significant relationships between facilitating condition and perceived ease of use and between facilitating condition and perceived usefulness was reported; and (3) the significant relationships among core components of TAM were found except for one, relationship between perceived usefulness and attitude.

1. Introduction

The Corona Virus Disease 2019 (Covid-19) pandemic has been very disastrous. As this manuscript was written, nearly 18 million cases were detected (World Health Organization, WHO, 2020). The magnitude effects of the virus have been very catastrophic; one of the effects is the school closures from the playground to Higher Education Institutions (HEIs). Responding to the pandemic, more than 100 countries around the world regulated national school closures. Even though, there has been no clear evidence that school closures could be effective to decrease the spread of viruses (Isfeld-Kiely and Moghadas, 2014). The closure has caused a massive use of online technology to improve distance learning.

The necessary to use technologies for educational purposes in education during the pandemic is inescapable; some current studies have addressed this issue (Mailizar et al., 2020; Kerres, 2020; Wang et al., 2020). One of the technologies used during the Covid-19 is e-learning, a media integration for instructions that utilizes a centralized platform to organize communication processes during instructional activities. E-learning from a computer-managed learning to collaborative online learning applies innovative technology platforms, such as Edmodo, Social media, Blog, Coursera, or specific platforms developed by HEIs. By using e-learning, students are expected to make significant development in doing their learning activities (Omar et al., 2011; Smith et al., 2008). The development of e-Learning in HEIs is commonly elaborated by two reasons, namely affordable cost and supporting facilities to foster learning effects (Clark and Mayer, 2016).

In normal condition, the aim of e-learning integration is to support face-to-face learning to be more flexible, efficient, and effective. Plethora studies have addressed the use of e-learning as the objects of research (e.g. Megahed and Mohammed, 2020; Kasraie and Kasraie, 2010; Pham et al., 2019; Ramírez-Correa et al.,. 2015; Shi et al., 2020). During the Covid-19, some recent studies regarding e-learning applications in

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education were also reported (Abbasi et al., 2020; Alamanthari et al.,. 2020; Favale et al., 2020; Radha et al., 2020). Nevertheless, studies regarding e-learning implementation are still limited in developing countries and in specific subject matters. Therefore, this study was conducted to understand factors predicting the use of e-learning through path analyses among Indonesian sport science education students. The study adapted Technology Acceptance Model (TAM) as a guiding academic model to understand the relationships between exogenous and endogenous constructs.

2. Literature review

2.1. Covid-19 and technology use in education

School doors have been shut in order to reduce the spread of the Covid-19. In accordance with the data, the closure has impacted more than 1.7 billion students across the world with 160 countries implemented the closures due to the pandemic (UNESCO, 2020). It can be computed that the Covid-19 has affected 91% or more of global learner population. At the same time, the crisis has opened an opportunity for the use of technologies as well as exposed to its challenges. On the other terms, it has given massive perspectives into the role of technologies in changing the learning process, supporting sustainable instruction, and facilitating students around the world with a medium of instruction during distance learning (Abbasi et al., 2020).

During the outbreak, massive efforts were attempted to make education run on the right track. Technologies can support remote learning; therefore, factors predicting its use during the pandemic are required to be evaluated and reported. Digital technologies, especially online technology, enables educational stakeholders to look for answers to what, where, when, and how students and teachers learn. More importantly, online technology can help increase teachers' role. Rather than just facilitating communication, teachers could be coaches, mentors, and evaluators (Akmaliyah et al., 2020). Online technology refers to technological tools that allow their users to information and communication access through the technology of World Wide Web (Wood and Smith, 2004).

2.2. E-learning in HEIs

The Covid-19 impacts on the ecosystem of the Internet have been reported by telecommunication companies and electronic engineering experts reported in academic journals, daily news, and blog posts. Microsoft posted about more than 700% increase of the cloud service use of the company emerged during the pandemic (Microsoft, 2020). Streaming quality has been reduced by Google and Netflix in order to prevent network overloads. While, Fastly as one of the biggest content delivery enterprises have been reporting an increase of 20–40% internet traffic since the implementation of lockdown in some countries (Cloudflare, 2020). In this paper, the reports of the study was supported by informing factors predicting the use of e-learning during the Covid-19 for a specific subject matter, Indonesian sport science education students.

E-Learning is an internet-based learning process in order to make students be more independent, improving student-centered learning (Schworm and Gruber, 2012). McArdle G, Bertolotto (2012) informed that learning courses operating the whole activity process by solely using e-learning earned higher dropout rates than that of traditional or face-to-face learning. E-learning is suggested to be utilized for many learning conditions with appropriate adjustments to the approach (Burgos et al., 2007). The repercussion of e-learning is widely influencing the performance of educational stakeholders, namely teachers or instructors and learners (Ramírez-Correa et al., 2019).

2.3. E-learning: TAM perspectives

Many scientific frameworks have been used to understand the integration of technology. Among the frameworks, TAM has been the most widely-used and reported model in the social science context (Teo et al., 2018). The TAM defines that the attitude; people's feeling, positive or negative, regarding the behavioral intention performance towards adopting a system is predicted by their perceived usefulness and perceived ease of use (Davis, 1989). In the original theory of TAM, perceived ease of use is also reported to predict perceived usefulness. Besides, behavioral intention (the degree to which people perform or not perform for specific future behavior) to adopt a system is predicted by the attitude and perceived usefulness. Finally, the actual use that is described as the use of a system is predicted by behavioral intention (Davis, 1989). Studies reported some external factors to accompany the original TAM constructs (Venkatesh and Bala, 2008; Venkatesh and Davis, 2000). Specifically, the TAM was extended in the reports of e-learning integration in education (Cakır and Solak, 2015; Mohammadi, 2015; Ramírez-Correa et al., 2019; Saade et al., 2007; Zhang et al., 2008). In this study, facilitating condition as the extended factor was proposed to hypothetically predict perceived ease of use and perceived usefulness.

2.4. Research model and hypotheses

To explore factors predicting the use of e-learning during the Covid-19 among sport science education students, an extended TAM-based framework was proposed. The proposed framework with eight Hypotheses is shown in Figure 1. Firstly, facilitating condition is introduced to become the only external variable to accompany the core TAM-based construct. It is defined as the degree to which sport science students' believe that organizational and technical resources exist to support the use of e-learning during the pandemic. Facilitating conditioned is hypothesized to have relationships with perceived ease of use (H1) and perceived usefulness (H2). Previously, facilitating condition was reported to significantly predict perceived ease of use for technology integration in education (Muhaimin et al., 2019; Nikou and Ecomides, 2017). In addition, it was also informed to be significantly related to perceived usefulness (Rahimi et al., 2015). Nevertheless, two previous studies by Muhaimin et al. (2019) Teo et al. (2018) confirmed that facilitating condition is an insignificant predictor for perceived usefulness.

Perceived ease of use as one of the main variables of the original TAM is described as the level to which sport science students' believe that the use of e-learning during the Covid-19 would be easy. It was hypothesized to predict perceived usefulness (H3) and attitude (H4). In the previous studies, it was one of the exogenous constructs to significantly predict perceived usefulness for e-learning use in instruction (Halawi and McCarthy, 2008; Ramírez-Correa et al., 2015; Mohammadi, 2015). In addition, perceived ease of use was also reported to be significant in predicting attitude (Buabeng-Andoh et al., 2019; Muhaimin et al., 2019).

Perceived usefulness was narrated as the level of sport science students' believes that the use of e-learning during Covid-19 would enhance work performance. Perceived usefulness was expected to have a statistically significant relationship with attitude (H5) and to behavioral intention to use e-learning during Covid-19 (H6). Mohammadi (2015) and Ramírez-Correa et al. (2015) revealed the strong correlation between perceived usefulness and intention to use e-learning. While, Buabeng-Andoh et al. (2019) and Muhaimin et al. (2019) pointed out that perceived usefulness was a key predictor of attitude.

Attitude in this study is expressed as Indonesian sport science students' certain behavior linked with the use of e-learning during Covid-19. The attitude was hypothesized to have a significant relationship with behavioral intention (H7). Mohammadi (2015) and Muhaimin et al.

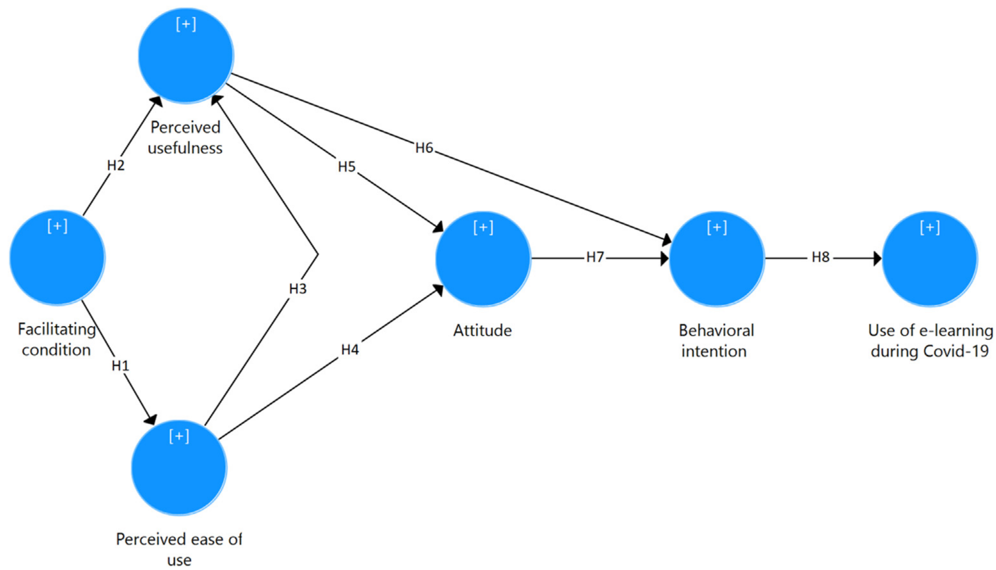

Figure 1. Proposed model.

(2019) reported that when the level of certain behavior linked with the use of technology was higher, the intention to use the technology would also be more significant. Finally, based on the TAM, behavioral intention was included, which is defined as Indonesian sport science students' intention to use e-learning during Covid-19. In this study, the behavioral intention is expected to have a statistically significant relationship with the actual use of e-learning during Covid-19 (H8). Previous studies revealed that behavioral intention were significantly correlated to the actual use of technology, especially e-learning (Ramírez-Correa et al., 2015; Teo, 2009).

3. Method

This study was done from May 2020 to July 2020 through an online survey when school closures were announced by Indonesian government started from May 20, 2020. Prior to the main data collection, a survey instrument to measure factors predicting the use of e-learning during Covid-19 among Indonesian sport science students was established and validated. The model measurement and assessment were done through the computation of the data in SmartPLS 3.2 that were guided by the procedures of Partial Least Squares Structural Equation Modeling (PLS-SEM). Regarding the ethical consideration of the study, the research was approved by the local ethics committee of the Lembaga Pengabdian dan Penelitian (LPPM), Universitas Jambi (Protocol Number: 078/UN.21.17/PP/2020).

3.1. Instrumentation

The review of literature provides researchers a guidance to address the definition and analysis of theories and concepts related to the theoretical research framework (Prasojo et al., 2020). It also aims at determining the objective approach for the instrumentation of the study. The instrument is made to address the research objectives (Habibi et al., 2020). In this study, adapted survey instruments were applied to measure factors predicting the use of e-learning during Covid-19 (Davis, 1989; Venkatesh and Bala 2008; Gunasekaran et al., 2002). Based on the adaptation process, the new instrument for the current study was established; the indicators differed, developed to suit the contexts of the study, Covid-19 and e-learning. In the first establishment process, 24 indicators were adapted for the instrument. The indictors were then discussed with three experts of educational technology from Malaysia and Indonesia through video conferences as part of content validity to make the instrument suit the context and setting of the study (Lynn 1986). After the video call meetings, ten indicators were revised while the two others were dropped due to unsuitable contexts; mostly because the topic of the research is about e-learning use during a pandemic that differs from the normal condition. To further evaluate the validity and reliability, the remaining indicators (22) were distributed for a pilot study to 100 sport science education students. Using SPSS 23, the data were computed for the evaluation of Cronbach's alpha, aiming to report the initial reliability before the main data collection. No construct has an alpha value below the threshold of .700 (Hair et al., 2019). Besides, a Varimax rotation was done to elaborate factors involved in the instrument through the procedures of exploratory factor analysis. In this procedure, some measurement explorations were implemented; Sphericity Bartlett Test that should be at $p < .005$, factor loading that should have a value of $\geq$.500, Kaiser-Meyer-Olkin with a value of $>$.800, and Communalities of $\geq$.300 (Courtney and Gordon, 2013; Pallant, 2020). The eigenvalue of $\geq$1.00 was proposed to understand the numbers of factors resulted in the process. One indicator from facilitating condition (FC4) was eliminated due to its shared variance of loading crossed to the other constructs, not in the facilitating condition. Meanwhile, other indicators meet the standardized measurement resulting on 21 indicators remained for the main data collection. From this process, six factors achieved eigenvalue of $\geq$1.00; Perceived ease of use, perceived usefulness, facilitating condition, attitude, behavioral intention, use of e-learning during Covid-19. The instrument was translated using back translation, English and Indonesian language (Behr et al., 2017). Both versions of the instrument are informed in Appendix 1 at the end of this manuscript.

3.2. Data collection

During the school closures, the survey instrument was distributed through an online survey application. The distribution of the data was done through Google Form, an application developed by Google Inc. The data were obtained from five Indonesian universities. The confirmation of permission letters for the data collection was issued by a public university in Indonesia. The school closures resulted in research during the Covid-19 to be limited to online. Spending a-two month time for the data collection, all respondents' answers were filed into Microsoft Excel and moved to the SmartPLS. To determine the sample, G*power was used with eight path lines or hypotheses proposed in the study, the sample is set to be more than 200 respondents. G*Power was founded as a program for statistical examination utilized by social and behavioral researchers providing established effect size calculators; it facilitates both distribution and design-based input types (Faul et al., 2007). Besides, a simple random sampling was implemented regarding the selection of sample (Altmann, 1974). Nine hundred and seventy four responses from Indonesian sport science students were obtained. Six hundred and four respondents were female, while 370 respondents were males. Three hundred and fifty-five respondents came from universities located in Java Island; six hundred and nineteen respondents were from universities in non-Java Islands.

4. Results

4.1. Measurement models

Measurement model refers to the evaluation procedures to test the measures' reliability as well as their validity. Three measurements were addressed; 1) indicator loadings and internal consistency reliability, 2) convergent validity, and 4) discriminant validity. The four measurements were suggested by Hair et al. (2019).

4.2. Indicator loadings and internal consistency reliability

PLS-SEM results were utilized for the indicator loadings in this study. Table 3 exhibits the detail of loadings. Most items achieved the recommended loading values of > .708 (Muhaimin et al., 2020). However, from the algorithm process in PLS-SEM, two indicators from the facilitating condition (FC4) and attitude (AT2) were dropped since both of them gained loadings of below .708 (Hair et al., 2019). Therefore, nineteen indicators remained for the next step within the PLS-SEM analysis. Internal consistency reliability refers to the evaluation findings for the statistical consistency across indicators. According to Hair et al. (2019), internal consistency reliability should be reported through Cronbach's alpha (α) and Composite Reliability (CR). The values of α and CR in this study implemented the threshold set by Hair et al. (2019); α should be >.700 and CR should be > .708. Table 1 shows the details of both measure values. The α and CR values for all construct shave good internal consistencies, the reliability ranging from .703 to .889 for the α and .830 to .923 for the CR.

4.3. Convergent validity

Convergent validity is a statistical issue that is linked with construct validity. Convergent validity suggests that assessments having the similar or same constructs should be highly related. Regarding the convergent validity, the scores of AVE must be reported. In calculating the scores, a PLS-SEM algorithm in the SmartPLS was utilized. The AVE scores should be ≥.500; it explains 50% or more of the variance. All constructs had an AVE score that is above .500 that explains more than 50% of the variance (Table 1).

4.4. Discriminant validity

Hair et al. (2019) stated that discriminant validity is the extent to which a construct is different from other constructs. By implementing the Fornell Larcker criterion, the AVE scores of a construct should be lower than the shared variance for all model constructs. From the results of the study, the AVE scores of every construct are lower than that it's shared variance (Table 2). Therefore, the discriminant validity was established based on the evaluation of the Fornell Larcker criterion.

Further, discriminant validity can also be evaluated through the examination of cross-loadings. When a loading value on a construct is bigger than those of all of its cross-loading values on the other constructs, the discriminant validity emerges. Table 3 performs that all indicators' values (bold) of the outer loading every construct were above the values of all their cross-loadings on the other constructs. Thus, discriminant validity emerged from the cross-loading value examination. Discriminant validity problems also appear when HTMT values are higher than .900. The construct can be similar if HTMT shows a value of > .900, lacks of discriminant validity. Table 4 informed that all values of HTMT were lower than .900. The results inform the values significantly differed from 1.

4.5. Structural model assessment

The structural model assessment includes some steps (Hair et al., 2019). The assessment process was begun with the computerization of collinearity by reporting Variance Inflation Factor (VIF) values. The relationship was examined in step two. In step three, coefficient of

Table 1. Reflective indicator loadings and internal consistency reliability.

	Item	Loading	α	CR	AVE
Attitude	AT1	.765	.703	.830	.620
	AT3	.785			
	AT4	.812			
Use of e-learning during Covid-19	AU1	.901	.799	.909	.832
	AU2	.924			
Behavioral intention	BI1	.820	.740	.851	.657
	BI2	.764			
	BI3	.845			
Facilitating condition	FC1	.843	.846	.907	.764
	FC2	.887			
	FC3	.892			
Perceived ease of use	PEU1	.870	.874	.913	.725
	PEU2	.832			
	PEU3	.831			
	PEU4	.871			
Perceived usefulness	PU1	.856	.889	.923	.750
	PU2	.852			
	PU3	.891			
	PU4	.865			

Table 2. Fornel larcker.

	Attitude	Behavioral intention	Facilitating condition	Perceived ease of use	Perceived usefulness	Use of e-learning during Covid-19
Attitude	.788					
Behavioral intention	.467	.810				
Facilitating condition	.557	.543	.874			
Perceived ease of use	.573	.685	.608	.851		
Perceived usefulness	.435	.673	.559	.687	.866	
Use of e-learning during Covid-19	.383	.624	.383	.569	.507	.912

Table 3. Cross-loading.

	Attitude	Behavioral intention	Facilitating condition	Perceived ease of use	Perceived usefulness	Use of e-learning during Covid-19
AT1	**.765**	.446	.609	.526	.427	.350
AT3	**.785**	.275	.285	.362	.255	.233
AT4	**.812**	.343	.346	.426	.304	.295
BI1	.440	**.820**	.543	.678	.562	.525
BI2	.346	**.764**	.337	.442	.450	.396
BI3	.348	**.845**	.424	.527	.606	.575
FC1	.474	.410	**.843**	.500	.420	.287
FC2	.475	.497	**.887**	.535	.524	.350
FC3	.512	.511	**.892**	.557	.515	.361
PEU1	.496	.603	.515	**.870**	.619	.522
PEU2	.486	.633	.556	**.832**	.681	.474
PEU3	.481	.506	.442	**.831**	.484	.464
PEU4	.486	.576	.546	**.871**	.534	.475
PU1	.423	.575	.510	.631	**.856**	.443
PU2	.386	.606	.454	.581	**.852**	.461
PU3	.387	.594	.526	.612	**.891**	.436
PU4	.299	.552	.440	.551	**.865**	.412
AU1	.340	.533	.323	.486	.425	**.901**
AU2	.359	.603	.373	.549	.495	**.924**

Table 4. HTMT.

	Attitude	Behavioral intention	Facilitating condition	Perceived ease of use	Perceived usefulness
Attitude					
Behavioral intention	.620				
Facilitating condition	.677	.674			
Perceived ease of use	.706	.836	.702		
Perceived usefulness	.522	.818	.639	.770	
Use of e-learning during Covid-19	.493	.796	.461	.677	.598

determination (R^2) was computed. In step four, the effect size of f^2 for the relevance of the construct was reported; it aimed at exploring the explanation of the selected endogenous constructs. Regarding the R2 and f^2effect size for the values of R^2, the data were also computed in PLS-SEM through blindfolding procedure in reporting the Q^2 values, step five and six.

4.6. Collinearity issue

The sets of predictors should be examined for collinearity. The collinearity is reported through the examination of VIF value. The collinearity will be an issue if the VIF value is reported to >3.000 (Hair et al., 2019). Attitude has a role as a predictor of behavioral intention

Table 5. VIF values.

	Attitude	Behavioral intention	Perceived ease of use	Perceived usefulness	Use of e-learning during Covid-19
Attitude		1.233			
Behavioral intention					1.000
Facilitating condition			1.000	1.587	
Perceived ease of use	1.895			1.587	
Perceived usefulness	1.895	1.233			

(VIF = 1.233). Behavioral intention is the predictor of the use of e-learning during Covid-19 (VIF = 1.000). Facilitating condition is the predictor of perceived ease of use (VIF = 1.000) and perceived usefulness (VIF = 1.587). Perceived ease of use is the predictor of attitude (VIF – 1.895) and perceived usefulness (VIF = 1.587). Lastly, perceived usefulness is the predictor of attitude (VIF = 1.895) and behavioral intention (VIF = 1.233). All values of VIF are below three (Table 5). Therefore, collinearity does not emerge as an issue in this study since all VIF values are less than 3 (Hair et al., 2019; Muhaimin et al., 2020).

4.7. Structural model relationship

To assess the path coefficient between endogenous and exogenous constructs, the sample was bootstrapped through 5,000 sub-sampling. Applying 5% level of significance, most hypotheses were supported but H5 (Table 6 and Figure 2). Perceived usefulness was not a significant predictor for attitude (β = .077; t = 1.084; p = .071). The strongest relationship emerged, supporting H8; behavioral intention significantly predicted use of e-learning during Covid-19 (β = .624; t = 23.757; p < .01) followed by the predicting role of facilitating condition to perceived ease of use, H1 (β = .624; t = 23.757; p < .01). Facilitating condition is also reported to have a significant effect on perceived usefulness (β = .224; t = 23.757; p < .01). In affecting attitude, perceived ease of use (H4) has a significant effect (β = .520; t = 11.894; p < .01). In addition, H3 was also supported; perceived ease of use is the significant predictor of perceived usefulness (β = .551; t = 15.876; p < .01). In predicting behavioral intention, two predictors, attitude and perceived usefulness, were reported to be significant; H6 (β = .551; t = 15.876; p < .01) and H7 (β = .216; t = 8.050; p < .01).

4.8. Coefficient of determination (R^2)

Coefficient of determination (R^2) is the output value of analysis of regression interpreted as the variance proportion in endogenous variables that can be predicted by the exogenous variable. It measures the predictive accuracy of a proposed model. It is counted as the squares correlation between a specific endogenous construct's. The R^2 ranges from 0 to 1; A higher value results in a higher level of R^2; .75 is substantial, .50 is moderate, and .25 is considered weak (Hair et al., 2019). From the results of the study, Table 7 performs the result of R2; attitude (.331, weak), behavioral intention (.490, moderate), perceived ease of use (.370, moderate), perceived usefulness (.504, weak), and use of e-learning during Covid-19 (.389, moderate). In conclusion, the results of R^2 show a sufficient level of R^2.

4.9. Effect size (f^2)

The effect size or f^2 is a concept in statistics about measuring the strong relationship of a predictor construct on an independent variable. In other words, f^2 is done measuring the effect of exogenous constructs to endogenous constructs. f^2 examines the change of R^2 value when a certain exogenous construct is removed from the model. According to Hair et al. (2019), the f^2 value of .02 is define a small effect, the value of .15 gains a medium effect, and the value of .35 is described to have a large effect. The findings of the study revealed seven correlational effect sizes. Facilitating condition to perceived usefulness gained the smallest effect while behavioral intention to use of e-learning during Covid-19 obtained the largest f^2, with a value of .638. One relationship, between perceived usefulness and behavioral intention, has no effect size (Table 8).

4.10. Predictive relevance (Q^2)

The predictive relevance denounced as Q^2 was reported through the Stone-Geisser'. If the model performs a predictive relevance, a study will show accuracy to predict the data points of items (Hair et al., 2019). The step to produce the Q^2 values was conducted in PLS-SEM using the blindfolding procedure. Q^2 values of higher than 0 indicated the establishment of the model's predictive relevance. Hair et al. (2019) suggest that the Q^2 value of .02 shows a small predictive relevance, the value of .15 informs a medium relevance, and .35 presents a large predictive relevance. The blindfolding result shows that perceived usefulness has the largest predictive relevance (Q^2 = .354) while attitude achieves the smallest predictive relevance of .185. Details of the Q^2 values of this study are presented in Table 9.

5. Discussion

To explore factors predicting the use of e-learning during Covid-19, a version of an extended TAM involved in this study has been successfully utilized to explain the process of the adoption of e-learning during Covid-19 perceived by Indonesian sport science education students from five HEIs. From the results, the scale can be examined and adapted by other researchers in the future who are interested in doing research on the area of technology integration, especially during pandemics like Covid-19 and based on virtual-based studies among HEIs students. The instrument helps to address a significant contribution to improving academic techniques for structural equation research. Through the content validity and measurement model, the model is reported to be valid and reliable. Previous studies used similar measurement in testing their scale (Mohammadi, 2015; Muhaimin et al., 2019; Ramírez-Correa et al., 2015).

Through bootstrapping process with 5,000 sub-samples, the findings of the study revealed that facilitating condition as the beliefs that organizational and technical resources exist to support the use of e-learning during Covid-19 has a significant relationship with perceived ease of use, confirming the 1st hypothesis of the current study. It can be inferred that the facilitating condition such as appropriate facilities, good environment, and easy access to the Internet would ease Indonesian sport science students to use e-learning during the lockdown. In normal time, facilitating condition was also reported to significantly predict perceived ease of use (Muhaimin et al., 2019; Nikou and Economides, 2017). A significant relationship between facilitating condition and perceived usefulness were presented for the model proving that the environment and

Table 6. Final result.

H		B	Mean	SD	t statistics	p values	Significance
1	Facilitating condition → Perceived ease of use	.608	.609	.036	17.039	p < .01	Yes
2	Facilitating condition →Perceived usefulness	.224	.224	.042	5.337	p < .01	Yes
3	Perceived ease of use → Perceived usefulness	.551	.550	.035	15.876	p < .01	Yes
4	Perceived ease of use → Attitude	.520	.521	.044	11.894	p < .01	Yes
5	Perceived usefulness → Attitude	.077	.077	.043	1.804	.071	No
6	Perceived usefulness → Behavioral intention	.579	.579	.024	23.706	p < .01	Yes
7	Attitude → Behavioral intention	.216	.216	.027	8.050	p < .01	Yes
8	Behavioral intention → Use of e-learning during Covid-19	.624	.625	.026	23.757	p < .01	Yes

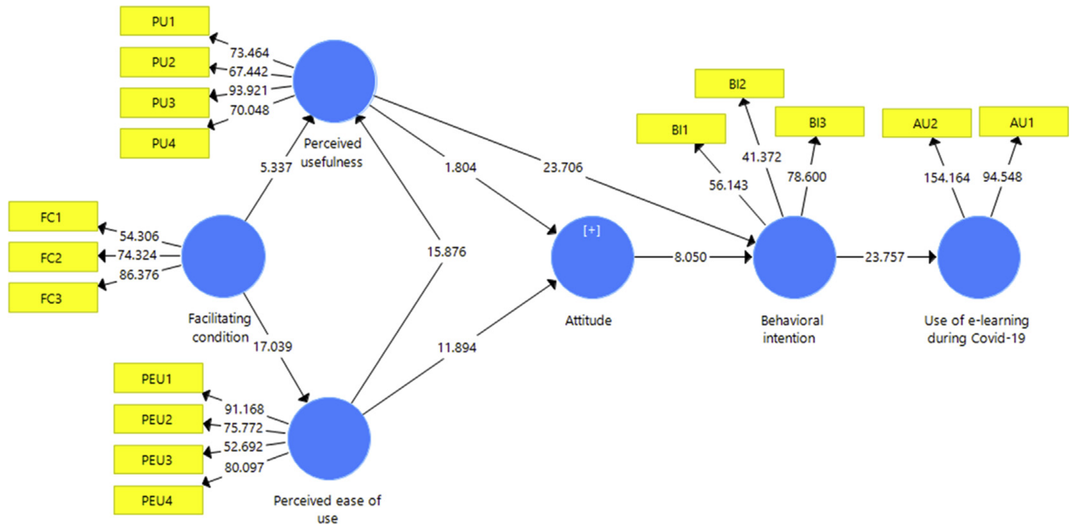

Figure 2. Final model.

Table 7. Coefficient of determination (R^2).

	R^2	Consideration
Attitude	.331	weak
Behavioral intention	.490	moderate
Perceived ease of use	.370	moderate
Perceived usefulness	.504	weak
Use of e-learning during Covid-19	.389	moderate

Table 8. f^2 result.

	f^2	Effect size
Attitude -> Behavioral intention	.074	Small
Behavioral intention -> Use of e-learning during Covid-19	.638	Large
Facilitating condition -> Perceived ease of use	.587	Large
Facilitating condition -> Perceived usefulness	.064	Small
Perceived ease of use -> Attitude	.213	Medium
Perceived ease of use -> Perceived usefulness	.386	Large
Perceived usefulness -> Attitude	.005	No effect
Perceived usefulness -> Behavioral intention	.533	Large

Table 9. Predictive relevance (Q^2).

	Q^2	Predictive relevance
Attitude	.185	Medium
Behavioral intention	.304	Large
Perceived ease of use	.250	Medium
Perceived usefulness	.354	Large
Use of e-learning during Covid-19	.309	Large

resource to use e-learning improve the beneficial impacts of the use of e-learning during Covid-19 perceived by Indonesian sport science students. The result contradicts a previous finding by Muhaimin et al. (2019) that found insignificant predicting power of facilitating condition to perceived usefulness for Web 2.0 integration.

Regarding perceived ease of use, the finding of this study reported that it significantly predict perceived usefulness; when e-learning is perceived to be user friendly, the respondents improve their feelings toward the benefit of the tools during the Covid-19. Similar reports from previous researchers confirmed this finding (Mohammadi, 2015; Ramírez-Correa et al., 2015; Zhang et al., 2008). Perceived ease of use is also reported to have a strong relationship with attitude; a shred of evidence that the more students think that e-learning is easy, the better they behave toward the use of e-learning during Covid-19. Buabeng-Andoh et al. (2019) through their meta–analysis study and Muhaimin et al. (2019) through their empirical data confirmed this finding. However, perceived usefulness was not a strong predictor of attitude. The result argued what Muhaimin et al. (2019) found; in their study, perceived usefulness was strongly correlated with attitude. The correlation between perceived usefulness and intention to use was found to be strongly significant. Other studies in e-learning integration also reported that when respondents' perceived that technology benefits instructional activities, the intention to use will be more likely to be improved (Nikou and Economides, 2017; Ramírez-Correa et al., 2015; Teo et al., 2018; Zhang et al., 2008).

In addition, the more attitude the respondents have toward the use of e-learning during Covid-19, the higher chance for them to learn using the tool. The significant relationship between attitude and intention to use technology in education was also reported by some previous studies (Mohammadi, 2015; Muhaimin et al., 2019). Finally, intention to use was reported to be significant in predicting the actual use of e-learning during Covid-19 which was supported by findings from Ramírez-Correa et al. (2015), Zhang et al. (2008), and Teo (2009). They also revealed that behavioral intention was a key predictor for e-learning use during teaching and learning processes. An attempt to make students more comfortable in using technology during pandemics like Covid-19 should always be promoted.

6. Conclusion

The TAM has been widely implemented to explore e-learning in HEIs in normal condition (Mohammadi, 2015; Ramírez-Correa et al., 2015; Zhang et al., 2008). These bulks of studies were evidence that e-learning has been implemented across countries around the world. However, a few studies investigated the use of e-learning during pandemics like Covid-19. Thus, the current study enriches academic literature in understanding the condition of distance learning during school closure due to pandemics, important guidance for future studies. Currently, due to the school closures, students' acceptance and use of e-learning is much more complicated and certainly unavoidable than that of normal conditions. Therefore, it is important to optimize the investment for e-learning in HEIs. The evaluation on factors affecting the use of e-learning during outbreaks like Covid-19 should be implemented for various contexts and settings. By focusing on sport science students' e-learning during Covid-19, most TAM-based relationships were confirmed to be significantly correlated. In addition, this study refers to the access aspects where not many students have adequate resources of technology that is related to facilitating condition, especially internet access. The results of the study need support from future researchers interested in doing similar types of research. Stakeholders should prepare better facing distance learning happened due to an outbreak. Although presenting the availability of statistical support, this research obtains some limitations. Respondents involved in this study are only from sport science education and from five universities; therefore, more respondents with different backgrounds of major are needed for future studies. Another interesting recommendation for future research is to understand the use of e-learning from qualitative perspectives through the interview or focus group discussions. Studies through comparative strategies are also recommended.

Declarations

Author contribution statement

S. Sukendro: Conceived and designed the experiments; Performed the experiments.

A. Habibi: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

K. Khaeruddin: Analyzed and interpreted the data; Wrote the paper.

B. Indrayana: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

S. Syahruddin: Contributed reagents, materials, analysis tools or data; Wrote the paper.

F. A. Makadada: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

H. Hakim: Performed the experiments; Wrote the paper.

Appendix I. Instrument (in English and Indonesian language) after measurement model assessment

	Facilitating Condition (FC)
FC1	When I need help using e-learning technology during distance learning (Covid-19), someone will help me
	Ketika saya butuh bantuan untuk menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) seseorang akan membantu saya
FC2	When I need help using e-learning technology during distance learning (Covid-19), someone will teach me
	Ketika saya butuh bantuan untuk menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19), seseorang akan mengajari saya
FC3	I will have the resources necessary for e-learning technology during distance learning (Covid-19)
	Saya akan memiliki sumber daya yang diperlukan untuk belajar dengan menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19)
	Perceived Usefulness (PU)
PU1	Using e-learning will improve learning performance during distance learning (Covid-19)
	Menggunakan e-learning akan meningkatkan kinerja belajar selama pembelajaran jarak jauh (Covid-19)
PU2	E-learning technology will increase my effectiveness during distance learning (Covid-19)
	Teknologi e-learning akan meningkatkan efektivitas saya selama pembelajaran jarak jauh (Covid-19)
PU3	E-learning technology will increase my productivity during distance learning (Covid-19)
	Teknologi e-learning akan meningkatkan produktivitas saya selama pembelajaran jarak jauh (Covid-19)
PU4	E-learning technology will be useful for me during distance learning (Covid-19)
	Teknologi e-learning akan berguna untuk saya selama pembelajaran jarak jauh (Covid-19)
	Perceived Ease of Use (PEU)
PEU1	Learning to use e-learning technology during distance learning (Covid-19) will be easy
	Belajar menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) akan mudah
PEU2	Using e-learning technology during distance learning (Covid-19) will be clear and easy to understand
	Menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) akan jelas dan mudah dipahami
PEU3	Using e-learning technology during distance learning (Covid-19) will be flexible to interact
	Menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) akan fleksibel untuk berinteraksi
PEU4	It will be easy to become skilled in using e-learning technology during distance learning (Covid-19)
	Akan mudah untuk menjadi terampil dalam menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19)
	Attitude (AT)
AT1	Using e-learning technology is a good idea during distance learning (Covid-19)
	Menggunakan teknologi e-learning adalah ide yang bagus selama pembelajaran jarak jauh (Covid-19)
AT3	I think using e-learning is a trend during distance learning (Covid-19)
	Saya pikir menggunakan e-learning adalah tren selama pembelajaran jarak jauh (Covid-19)
AT4	The e-learning technology will be compatible with the smart devices I use during distance learning (Covid-19)
	Teknologi e-learning akan kompatibel dengan gawai pintar yang saya gunakan selama pembelajaran jarak jauh (Covid-19)
	Behavioral Intention (BI)
BI1	I will use e-learning technology during distance learning (Covid-19) in the future
	Saya akan menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) di masa depan
BI2	I plan to use for e-learning technology during distance learning (Covid-19) in the future
	Saya berencana untuk menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) di masa depan
BI3	I would recommend using e-learning technology during distance learning (Covid-19) in the future
	Saya akan merekomendasikan penggunaan teknologi e-learning selama pembelajaran jarak jauh (Covid-19) di masa depan
	Use of e-learning during Covid-19 (AU)
AU1	I use e-learning technology during distance learning (Covid-19)
	Saya menggunakan teknologi e-learning selama pembelajaran jarak jauh (Covid-19)
AU2	I use e-learning technology to find information during distance learning (Covid-19)
	Saya menggunakan teknologi e-learning untuk mencari informasi selama pembelajaran jarak jauh (Covid-19)

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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