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Applying UTAUT Model to Understand Use of Behavior Health Applications User in Indonesia During the COVID-19

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ABSTRACT

This study examines the adoption of the PeduliLindungi application during the COVID-19 pandemic in Indonesia using the UTAUT paradigm. The data was submitted by 200 users of the PeduliLindungi app. SEM-PLS was used to analyze the relationships between the variables and assess several hypotheses. To enlarge the scope of the investigation, Importance-Performance Map Analysis (IPMA) and Multi-Group Analysis (MGA) were also looked at as moderating variables. The findings revealed that facilitating settings had no discernible impact on how people use the PeduliLindungi application, whereas performance expectation, effort expectation, and social influence all positively affect behavioral intention and usage behavior. Second, the proposed model was not significantly impacted by gender, age, or educational attainment. Third, social influence is more significant in behavioral intention but less significant in use behavior components, performance expectation is more significant in use behavior, and effort expectancy is more prominent than other dimensions in behavioral intention. The contribution of this research is to provide a broader perspective in understanding the adoption of PeduliLindungi application so that it can convey a review of the policy implications for technology adoption in Indonesia.

A. INTRODUCTION

The usage of various digital technologies, including internet-based services, to connect, interact, and conduct work from home, has increased dramatically in the COVID-19 Pandemic era (Chen, Y., & Zhang, Y.,2020). `People are more inclined to adjust their preferences and behavior patterns as a result of the restriction on interaction, such as moving to online shopping and different pick-up and delivery choices (Ferreira, J., Correia, A., & Duque, E. (2021). (Ferreira et al., 2011). In the health sector, this condition led to the expansion of the use of technology for various purposes such as prevention, diagnosis, screening, tracing, and contact tracing (Srinivasa Rao & Vazquez, 2020). In overcoming the spread of COVID-19, the Indonesian government created an application that can help government in the interests of tracking the spread of COVID-19 called "PeduliLindungi" (Putri & Hamzah, 2021). The PeduliLindungi application has 3 main functions, namely to carry out screening, tracing, and protecting

the public when accessing public facilities to be safe and avoid transmission of COVID-19 (Herdiana, 2021).

The COVID-19 pandemic that came suddenly caused the use of the PeduliLindungi application to face various obstacles, and advantages especially the practical adoption of technology in a relatively short time. Under these conditions, people's adoption of technology is an important issue, and technology adoption has become a broad field of research in all social sectors, including education, business, health, and social interaction (Liu & Miguel-Cruz, 2022).

Various theories have been developed to assess individuals' behavioral intention and technology usage when utilizing technology. One such theory is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Akar & Mardikyan, 2014). The UTAUT model stands out among other theories as it integrates elements from eight separate models into a comprehensive framework. This integration allows the UTAUT model to provide a more holistic understanding of technology adoption and use. Additionally, research has shown that the UTAUT model performs better than the other eight models, explaining up to 70% of the variability in user behavior (R2 = 70) (Eutsler, 2018).

The choice of the UTAUT model in our study is based on its widespread adoption and recognition within the field of technology acceptance and usage. By utilizing the UTAUT model, we can analyze the factors that influence individuals' behavioral intention and actual use of the PeduliLindungi application. The UTAUT model considers key determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions, providing a comprehensive framework to examine technology adoption and usage behavior. By incorporating the UTAUT model, our study aims to enhance the understanding of the factors that impact the adoption and usage of the PeduliLindungi application, contributing to the existing body of knowledge on technology acceptance and usage in the context of public health applications

Unified Theory of Acceptance and Use of Technology (UTAUT) is chosen as one of the most widely used and commonly employed theories in explaining the use and adoption of technology, both in organizational and individual contexts (Akbar et al., 2019). The UTAUT model offers several advantages that contribute to its popularity and extensive application. Firstly, it integrates elements from various existing theories, allowing for a comprehensive understanding of technology acceptance and usage. This comprehensive nature of the UTAUT model makes it suitable for analyzing complex phenomena and capturing multiple factors that influence technology adoption. Additionally, the UTAUT model has demonstrated robustness and generalizability through successful replications in different conditions of technology adoption across various fields (Venkatesh et al., 2016).

By utilizing the UTAUT model in our study, we leverage these advantages to gain a comprehensive understanding of the factors influencing the adoption and usage of the PeduliLindungi application. The UTAUT model enables us to examine key determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions, providing a robust framework for analyzing technology adoption and usage behavior.

Therefore, the selection of the UTAUT theory in our study is based on its widespread usage, the integration of various theories, and its proven applicability across diverse technological contexts. These advantages make the UTAUT model a suitable choice for investigating the adoption and usage of the PeduliLindungi application in the context of the COVID-19 pandemic.

Research on user adoption of applications in the Covid-19 era has been carried out by many researchers. Such as Application in Improving the Quality of Health Services During the COVID-19 (Gustiawan et al., 2023; Sujarwoto et al., 2022), research on mobile health (Zamberg et al., 2020; Abaza & Marschollek, 2017). Research using the UTAUT paradigm has also been carried out a lot, such as research on exploring the role of quality measurement in promoting the use of m-learning systems during COVID-19 (Almaiah et al., 2022), research on m-payment adoption during the co-19 pandemic (Yoebrilianti et al., 2022; Wei et al., 2021), risk Assessment Mobile Application (Yuduang et al., 2022), adoption technology (Handoko, 2020), however, there has been no research using the UTAUT paradigm which also identifies the importance performance map analysis as well as testing the moderating variable with multi group analysis.

Using the UTAUT model, this research is expected to predict and explain the intentions of the community who use the PeduliLindungi application. Several moderation factors, namely gender, age, experience, and voluntarism influence Behavioral Intentions, together with four main variables (Venkatesh & Smith, 2003). In recent years, the UTAUT model has been widely used to describe user intentions and uses. This model is used quite a lot to assess user acceptance of various applications such

as social media applications by non-profit organizations (NPOs) (Albanna et al., 2022), online food delivery applications (Allah Pitchay et al., 2022), Human pose estimation (HPE) (Miranda Difini et al., 2022).

This study's objectives are to determine the adoption of the PeduliLindungi application, which was created to address and halt the COVID-19 outbreak in Indonesia, and to look at the key aspects of user acceptance from the user's point of view. The following categories, in particular, best describe how the study's objectives might be divided: Survey overall user acceptance to answer research hypotheses, find the things that concern users the most through the analysis of influencing factors through Important Performance Map Analysis, analyze influence factors and group differences to identify potential users to help governments develop future strategies. In addition, this article will provide input for stakeholders in the implementation of the PeduliLindungi application in the future.

B. METHOD

In this study, a purposive sampling method was utilized, and questionnaires were employed to assess each component of the UTAUT architecture. The questionnaire was administered online to users of the PeduliLindungi application across various regions of Indonesia. The data collection period took place in June 2022, spanning three weeks. The decision to collect data in June 2022 was based on considerations such as the availability of participants and the relevance of the data collection period to the research objectives.

The choice of an online questionnaire technique was deemed appropriate for this study due to its convenience and wide reach, enabling the inclusion of participants from different geographical locations. Online questionnaires have been widely used in previous research and have shown to be effective in gathering data on technology acceptance and usage.

The sample size of 200 respondents was determined based on considerations of statistical power using the Partial Least Square Structural Equation Model (PLS-SEM) equation model. The sample size calculation was conducted using G*Power to ensure the sample size met the required statistical power of 0.8. In this study, the sample's statistical power exceeded the required value, reaching 0.95, thus providing sufficient statistical power for the analysis. The appropriateness of the sample size was further supported by previous research (Carranza et al., 2020).

While the purposive sampling method allows for the intentional selection of participants who possess relevant characteristics or experiences related to the research objectives, it may have limitations in terms of representativeness. However, the focus of this study is to gain insights from specific users of the PeduliLindungi application, and the purposive sampling method aligns with this objective.

Overall, the research design incorporated a purposive sampling method and an online questionnaire technique to collect data from 200 respondents. The chosen sample size and data collection period were based on considerations of statistical power, feasibility, and relevance to the research objectives. These decisions were informed by previous research and methodological justifications, ensuring the adequacy and appropriateness of the research design.

1. Characteristics of Respondents

Of the total respondents of 200 people, the comparison from the gender aspect was male (30.5%) and female (69.5%). Meanwhile, of the educational qualifications, 62% have Primary and Secondary education qualifications (elementary, junior high, high school/equivalent) and 38% have Higher Education qualifications (D4, Undergraduate, and Postgraduate). In terms of age, 63.5% were between the ages of 15 -25, and 36.5% were aged 26-46.

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2. Research and measurement instruments

The constructs were rated on a five-point Likert scale, with a value of 1 meaning "strongly disagree" and a value of 5 means "strongly agree". Age, gender, and education-related demographic questions are also provided. Thirty elements make up the four UTAUT constructs, which are used to assess technological readiness when using the PeduliLindungi application (Venkatesh & Smith, 2003). The social impact scale is made up of seven items, the performance expectation scale is made up of seven, the effort expectancy scale is made up of four, the facilitating condition has five items, behavioral intention has three, and use behavior could have up to four.

3.Data analysis

Using PLS-SEM analysis, a comprehensive multivariate statistical analysis method, all interactions between variables in a conceptual model, including measurements and structural elements, are examined concurrently in this work. Measurement models and structural models were assessed using a two-step procedure that adhered to the PLS-SEM analytic literature. R2, f2, Q2, and path coefficients are used to evaluate the structural model, while the validity and reliability of reflective constructs are used to evaluate the measurement model.

Multi Group Analysis was used to test whether there were any significant differences in the moderation variables and to test the pathway efficiency of the moderation variables (Kock, 2014). Comparing pairs of path coefficients for identical models based on various samples is one of the main goals of this type of analysis. In order to determine which independent constructs are highly relevant to the dependent construct, the performance of each independent construct was then calculated using Important Performance Map Analysis (IPMA.

4. Latent variables

By modeling behavioral intention against use behavior, the UTAUT model's four fundamental variables—performance expectation, effort expectancy, social influence, and facilitating condition—assist in understanding the mechanisms underlying behavior. The UTAUT model also takes into account how personal characteristics like gender, age, experience, and voluntarism of use might be moderated. In this study, we chose to replace experience and voluntarism with education as one of the intermediate variables in the UTAUT model. This decision was made because the PeduliLindungi application is relatively new and was released during an unusual and unprecedented moment, the COVID-19 pandemic. Given this context, the level of experience and voluntarism may not have a significant impact on the adoption and usage of the application (Ye et al., 2020). Therefore, we opted to include education as an intermediate variable in the model to capture its potential influence on technology acceptance and usage.

The UTAUT model utilized in this study comprises three moderator factors and six latent variables. We specifically included the moderator factors of age, education level, and gender in the hypotheses to examine their potential moderating effects on the relationships within the model. These moderator factors allow us to explore how age, education level, and gender may influence the relationships between the latent variables in the UTAUT model.

By incorporating these moderator factors, we aim to provide a more nuanced understanding of the complex interplay between individual characteristics and technology adoption behavior in the context of the PeduliLindungi application. This approach allows us to explore potential variations in the relationships within the UTAUT model based on age, education level, and gender, providing valuable insights into the factors that may influence technology acceptance and usage.

Therefore, the inclusion of education as an intermediate variable and the incorporation of the moderator factors of age, education level, and gender enhance the comprehensiveness of our analysis,

enabling a deeper examination of the UTAUT model's relationships in the context of the PeduliLindungi application.

5. Moderator variables

In this study, age, gender, and educational attainment were considered as moderator variables. These variables were chosen based on previous research that suggests their influence on the rate at which individuals adopt new technologies. The inclusion of these moderator variables in the study aims to test the predictions of the model and examine how age, gender, and educational attainment may impact the adoption of the PeduliLindungi application. By considering these variables as moderators, we can gain insights into the potential variations in technology adoption behavior and assess whether the relationships within the model differ across different age groups, gender identities, and educational backgrounds.

1) Age

Physical, psychological, cognitive, and emotional abnormalities can result from age differences. Age disparities are thought to affect how people accept information technology (Venkatesh & Smith, 2003). People of different ages will adopt new information technologies with varying attitudes, perceptions, and behaviors. Younger people have better memory and learning skills than older people do, and they are also more curious. As a result, it is simpler to take a positive outlook when embracing new technologies. Older users take longer to accept changes because they want consistency in their work.

2) Gender

Differences in appearance are frequently influenced by gender. Women rely more on engagement and conversation with people when studying information technology than men do since males are ridiculed and doubtful when they realize something, evaluate, and confirm the knowledge. The number, kind, and usage of phones and applications are significantly influenced by gender (Andone et al., 2016).

3) Education

The degree of education a person has will determine how well they are able to comprehend and accept new concepts. Although understanding it is thought to be more difficult and people with higher levels of education should have a more positive attitude toward it, accepting and using PeduliLindungi is thought to be relatively simple.

6. Research hypothesis

Based on the foregoing, the study proposes six hypotheses:

H1: Performance Expectation has a positive influence on Behavioral Intention
H2: Effort Expectancy has a positive influence on Behavioral Intention
H3: Social Influence has a positive influence on Behavioral Intention
H4: Facilitating Condition has a positive influence on Use Behavior
H5: Behavioral Intention has a positive influence on Use Behavior
H6: Group Differences affect the Path Coefficient

7. UTAUT model structure diagram

Figure 1 depicts the UTAUT model's structure diagram in accordance with the research hypothesis.

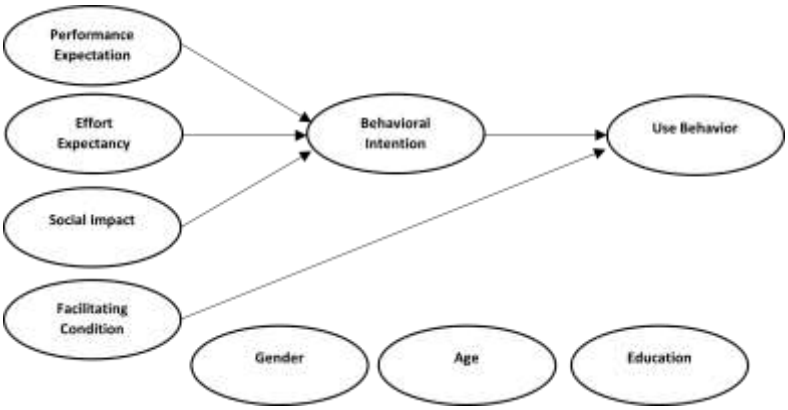

Figure 1.

Structural Diagram model of UTAUT

Source: modified from Venkatesh & Smith, 2003

8. Model construction

The statistical program SmartPLS 3.2.7 was employed in this work to estimate model parameters and test hypotheses. We construct a diagram of logical connections between variables based on the hypothesis, as shown in Figure 1. Analyze and investigate the impact of Behavioral Intention (BI) and Use Behavior (UB) on Performance Expectation (PE), Effort Expectancy (EE), Social Impact (SI), and Facilitating Condition (FC).

C. RESEARCH FINDINGS AND DISCUSSION

1. Measurement model

The validity and reliability of the proposed model were initially assessed by analyzing the measurement model. Construct dependability was evaluated using composite reliability (CR) and Cronbach's alpha. According to Cronbach (1951), internal consistency dependability is demonstrated by a Cronbach's alpha score greater than 0.7. Cronbach's alpha is a widely used measure to assess the reliability and internal consistency of a scale or questionnaire.

The findings show that all constructs have Cronbach's alpha values ranging from 0.703 to 0.922, indicating a high degree of reliability. The recommendations made by Hair et al. were followed in this study to evaluate the overall reliability and validity of all latent variables. When assessing composite reliability, the CR cut-off value should be 0.7 or higher. The results demonstrate that every construct has a CR greater than 0.7, indicating good reliability. All constructs have an average variance extract (AVE) greater than 0.5 for convergence validity.

The finding shows that all structures had a CR higher than 0.7, which provided good dependability. All constructs showed average variance extracted (AVE) values larger than 0.5, which satisfied the requirements for convergent validity. All factor loadings for all 30 items were above 0.5, according to the CFA results, suggesting convergent validity for all latent variables. Finally, for good convergent validity, the value of AVE should be greater than 0.50. The research revealed that the value of AVE varied between 0.612 and 0.819, indicating that all constructs satisfied the requirements for convergent validity. Table 1 provides an overview of the factor loading, CR, and AVE results. The validity of discrimination was then looked at. According to Fornell and Larcker (1981), discriminant validity is indicated by the square roots of AVE being significantly higher than the correlations below the diameter (Fornell & Larcker, 1981). Table 2 demonstrates that every construct has a square root of AVE value greater than any correlation between any two constructs.

Table 1.
The result of the measurement model

Construct/item	Loading	Cronbach' Alpha	Dijkstra–Henseler's rho (ρA)	Cr	Ave
Performance Expectation		**0,824**	**0,904**	**0,917**	**0,612**
	0,730				
Using the PeduliLindungi application can increase productivity when carrying out activities	0,848				
Using the PeduliLindungi application can make it easier to do activities and not be convoluted	0,760				
Using the PeduliLindungi application can speed up activities	0,802				
Using the PeduliLindungi Application will produce quality output	0,797				
Using the PeduliLindungi Application makes activities easier than before using the PeduliLindungi Application	0,703				
The PeduliLindungi application meets my expectations to be safer and more comfortable in carrying out activities in public spaces	0,828				
Effort Expectancy		**0,926**	**0,931**	**0,948**	**0,819**
The features in the PeduliLindungi application are simple so that it is easy to understand	0,913				
Features in the PeduliLindungi application are simply easy to learn	0,922				
The features in the PeduliLindungi application are simple so it is easy to run	0,932				
The interaction between users and the PeduliLindungi application is clear so it is very easy to understand	0,851				
Social Influence		**0,902**	**0,915**	**0,923**	**0,633**
I use the PeduliLindugi app because my friend uses	0,803				
I use the PeduliLindugi app because my family uses	0,833				
I use the PeduliLindugi application because of the applicable policies	0,732				
I use the PeduliLindugi application because of the influence of the organization	0,857				
I use the PeduliLindungi application because of the influence of social media	0,864				
I use the PeduliLindugi application because my surroundings have used the PeduliLindungi application a lot	0,718				
Using the PeduliLindungi application can improve my self-image	0,745				
Facilitating Condition		**0,889**	**0,906**	**0,918**	**0,693**
I have the facility to access the PeduliLindungi application (*smartphone*)	0,827				
I have enough ability and knowledge to use the PeduliLindungi application	0,856				
In the PeduliLindungi application, there is a usage guide so I can easily understand	0,887				
Some experts can help me when I have trouble using the PeduliLindungi application	0,787				
I feel that the PeduliLindungi application is a system that can work accordingly	0,801				
Behavioral Intention		**0,861**	**0,874**	**0,915**	**0,783**

I intend to use the PeduliLindungi App more often	0,834				
PeduliLindungi application is a very good service	0,910				
PeduliLindungi application provides excellent service (very good)	0,903				
Use Behavior		**0,824**	**0,870**	**0,881**	**0,651**
I use the PeduliLindungi application every time there is a QR scan	0,854				
I use the PeduliLindugi application when requested by the officer	0,864				
I use the PeduliLindungi application when someone is alerting	0,715				
I use the PeduliLindungi application if the situation and conditions are precarious	0,786				

Source: analysis result

Construct/item	Loading	Cronbach' Alpha	Dijkstra–Henseler's rho (ρA)	Cr	Ave
Performance Expectation		**0,824**	**0,904**	**0,917**	**0,612**
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Social Influence		**0,902**	**0,915**	**0,923**	**0,633**
Facilitating Condition		**0,889**	**0,906**	**0,918**	**0,693**
Behavioral Intention		**0,861**	**0,874**	**0,915**	**0,783**
Use Behavior		**0,824**	**0,870**	**0,881**	**0,651**

Source: analysis result

The measurement model analysis revealed strong associations between the construct items and their respective constructs. Constructs such as Performance Expectation, Effort Expectancy, Social Influence, Facilitating Condition, Behavioral Intention, and Use Behavior displayed high loadings and demonstrated good internal consistency reliability, as evidenced by high Cronbach's alpha values (ranging from 0.861 to 0.926). These findings support the validity and reliability of the measurement model.

Table 2.
Discriminant Validity

		BI	EE	FC	PE	SI	UB
Fornell–Larcker criterion	BI	*0.885*					
	EE	0.579	*0.905*				
	FC	0.441	0.403	*0.847*			
	PE	0.587	0.583	0.270	*0.783*		
	SI	0.380	0.175	0.031	0.214	*0.795*	
	UB	0.394	0.244	0.251	0.190	0.242	*0.807*
Heterotraite-monotraite (HTMT) ratio	BI	0.642					
	EE	0.505	0.452				
	FC	0.654	0.637	0.306			
	PE	0.430	0.195	0.093	0.235		
	SI	0.442	0.258	0.273	0.200	0.288	

Source: analysis result
Note: The square root of the AVE is displayed diagonally in italics; UB: Use Behavior; BI: Behavior Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectation; SI: Social Influence

According to the Fornell-Larcker criterion, the correlations between the constructs should be smaller than the square root of the average variance extracted (AVE) of each construct. In this table, all correlation coefficients between the constructs are smaller than the square root of the AVE of each construct, indicating adequate discriminant validity.

The HTMT ratio is used to compare the correlations between constructs against a specific threshold to assess discriminant validity. In this table, all HTMT ratios between the constructs are smaller than 1, indicating satisfactory discriminant validity.

In summary, the results of this table demonstrate that the constructs in the model have adequate discriminant validity, indicating that they are distinct and not highly correlated with each other in the context of this study.

2. Structural models

To make sure that there is no bias in the regression results, the colinearity should be examined before investigating the structural relationship. The variance inflation factor (VIF) would be below 3 in an ideal scenario (Hair et al., 2019). Because the VIF value was below the established limit, this study found no collinearity issues. Testing will then proceed to the structural model evaluation. The importance of indicators and path coefficients was assessed using the bootstrap approach with 5,000 iterations (Chin et al., 2008). An evaluation of the model's quality is performed before hypothesis testing. The criteria include the cross-validated redundancy (Q2), the path coefficient, the coefficient of determination (R2), and the effect size (f2) (Hair et al., 2019). For all endogenous structures, R2 is 0.75, 0.50, and 0.25, corresponding to considerable, medium, and weak structures, respectively. The findings revealed that R2 for Use Behavior was 0.156 and R2 for Behavior Intention was 0.368. This suggests that exogenous variables with low criteria are influencing each of these variables.

Calculating f2 with criteria of 0.02 (small), 0.15 (mid), and 0.35 (big) will reveal the effect size for each path model (Hair et al., 2019). All path models for behavioral intention include moderate criteria: performance expectation (0.142), effort expectation (0.149), and social influence (0.114). Behaviour Intention has a medium effect size (0.119) while in Use Behavior, while Facilitating Condition has a low effect size (0.011).

The evaluation of structural models was concluded by applying Stone-Geisser's Q2 to determine the model's predictive usefulness. All Q2 values are greater than zero as shown by the results (see Table 3), indicating the model has respectable predictive power.

Table 3.
Structural Model Evaluation

Relationship	β	T Value	Variance explained (R2)	R2 adjusted	Predictive relevance (Q2)	Effect size (f2)	VIF
BI->UB	0,349	3,616	0.488	0.480	0.363	0.119	1.219
EE->BI	0,340	4,136				0.149	1.520
FC->UB	0,108	1,246^{ns}	0.165	0.156	0.990	0.011	1.219
PE->BI	0,335	4,809				0.142	1.545
SI->BI	0,248	3,937				0.114	1.052

Source: analysis result

Table 4 displays the outcomes of one-way hypothesis testing. One-way testing is advised if the coefficient is believed to have a sign (positive or negative) (Kock, 2014). As a result, H1, H2, and H3 are accepted. Performance expectation positively affects behavioral intention (=0.349, t=3.616), effort expectation positively affects behavioral intention (=0.340, t=4.136), and social influence positively affects behavioral intention (=0.248, t=3.937). H4 is rejected because the Facilitating Condition has no effect on Use Behavior (=0.108, t=1.246). H5 is accepted because behavioral intention affects use behavior (=0.349, t=3.616).

Table 4.
Result of hypothesis testing

Relationship	β	T Value	Supported
H1 : PE->BI	0,335	4,809	Yes
H2 : EE->BI	0,340	4,136	Yes
H3 : SI->BI	0,248	3,937	Yes
H4 : FC->AU	0,108	1,246^{ns}	No
H5 : BI->AU	0,349	3,616	Yes

Source: analysis result

3. Analysis of group differences

The grouping criteria in this study were based on gender, age, and educational attainment. Each element can be separated into two groups to guarantee that the subsample has an adequate sample size, including the sex grouping of males and females and the age grouping of young people (15–25 years old) and adults (26–46 years old). Meanwhile, there are two categories of education: basic and secondary education, and higher education. The route coefficients of various groups are computed using the UTAUT model.

Based on the results of the analysis presented in Table 5, for male and female users, the main difference is reflected in the Facilitating Condition of Use Behavior where men have a much greater influence than women. From the aspect of age, the calculation results show that there is no significant difference between young and more mature users. Meanwhile, from the aspect of education, there is a significant difference between secondary primary education and higher education, where postgraduate users have a higher level of performance expectation of behavioral intention than users with primary and secondary education levels. From the results of the calculation of the moderator variables, it can be concluded that in general the factors of gender, age and education do not affect the path coefficient so Hypothesis 6 is rejected.

Table 5.
Group Analysis Result

Influence Path	*P*	Standardization Coefdicient	*P*	Standardization Coefdicient	C.R	Difference
Gender	Male		Female			
BI -> UB	0.218	0.165	0.430	0.120	0.295	Not Significant
EE -> BI	0.339	0.145	0.328	0.094	0.954	Not Significant
FC -> UB	0.344	0.140	-0.011	0.108	0.033	Significant
PE -> BI	0.427	0.156	0.282	0.092	0.451	Not Significant
SI -> BI	0.204	0.094	0.284	0.087	0.528	Not Significant
Age	15-25		26 - 46			
BI -> UB	0.329	0.122	0.411	0.149	0.656	Not Significant
EE -> BI	0.335	0.103	0.351	0.130	0.919	Not Significant
FC -> UB	0.142	0.103	0.039	0.170	0.594	Not Significant
PE -> BI	0.303	0.100	0.398	0.124	0.568	Not Significant
SI -> BI	0.227	0.081	0.306	0.098	0.528	Not Significant
Education	Under Graduate		Post Graduate			
BI -> UB	0.404	0.129	0.249	0.167	0.464	Not Significant
EE -> BI	0.428	0.096	0.176	0.100	0.076	Not Significant
FC -> UB	0.110	0.120	0.141	0.153	0.807	Not Significant
PE -> BI	0.180	0.087	0.633	0.094	0.000	Significant
SI -> BI	0.302	0.086	0.137	0.069	0.139	Not Significant

Source: analysis result

4. Impact–Performance Map Analysis (IPMA)

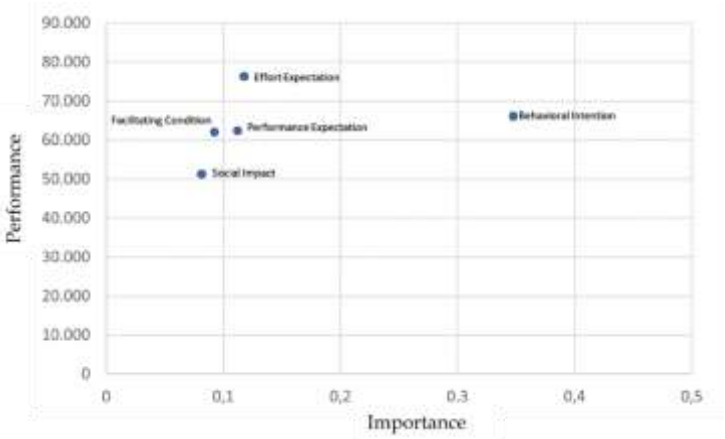
The IPMA for the variables Behavioral intention and Use Behavior is shown in Table 6. The objective is to discover structures that are comparatively underperforming yet relatively significant for the desired construct (Henseler et al., 2015). For constructing behavioral intention, there is a first IPMA. Among the behavioral intention dimensions, effort anticipation is more significant (0.340) than the others. Because they are the most significant and perform better than average, effort expectation-related factors must be given priority to increasing behavioral intention. Comparatively speaking, social Influence performs the worst (57,914) in the behavioral intention construct (Figure 3). Use behavior is covered by the second IPMA. Performance expectation has a greater relevance level (0.352) than other use behavior elements. As a result, as they are the most significant and have the average performance, performance expectation-related factors must be given top consideration in order to optimize usage behavior. Social impact also performs the worst out of all the constructs in the use behavior construct (0.088).

Table 6.
Importance–Performance Map

Constructs	Behavioral Intention		Use Behavior	
	Importance	Performance	Importance	Performance
Performance Expectation	0.335	68.660	0.118	68.660
Effort Expectation	0.340	77.929	0.120	77.929
Social Influence	0.248	57.914	0.088	57.914
Facilitating Condition			0.095	68.053
Behavioral Intention			0.352	67.009

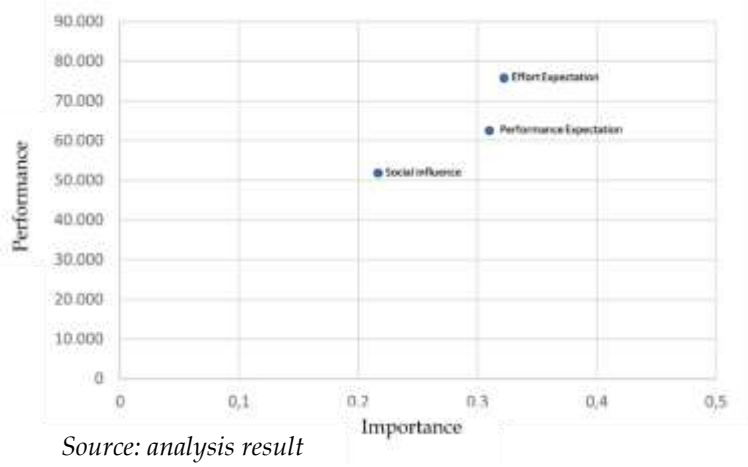
Source: analysis result

Figure 3.
IPMA of Use Behavior



Source: analysis result

Figure 4.
IPMA of Component of Behavioral Intention



Source: analysis result

Discussion

A model expansion employing IPMA analysis and moderator factors has been validated and proven to explain Utilize Behavior to use the PeduliLindungi application, which will help us understand how people used technology during the COVID-19 Pandemic. The findings demonstrated that behavioral intention to use the PeduliLindungi application is formed in part by performance expectation and effort expectancy.

These findings support the finding of earlier researchers by demonstrating that a person's attitude toward using the PeduliLindungi application improves the more he believes it has performed as expected and is simple to use. The findings additionally demonstrate how behavioral intention impacts

use behavior (Zeebaree et al., 2022). The R Square behavioral intention test on use behavior revealed positive results (0.488), but the R Square facilitating condition test on use behavior revealed a negligible value. It can be said that there are still other factors that influence use behavior, such as online spiritual meets (OSM) (Katoch & Rana, 2023), trust (Hooda et al., 2022), perceived ease of use and perceived enjoyment exerting (Bai & Guo, 2022). Technology adoption during the COVID-19 pandemic is influenced by a number of factors, including perceptions of usability and ease of use as well as the fear of contracting the disease (Al-Maroof et al., 2020)

The PeduliLindungi application supports the social isolation necessitated by the COVID-19 outbreak. Therefore, people will adopt the PeduliLindungi application more quickly if it is useful and simple to use during a pandemic. By emphasizing the crucial roles that perceived benefits and perceived usability played in the adoption of apps during the COVID-19 pandemic, the study adds to the body of literature.

Another thing from the results of this study is that facilitating conditions do not have a significant influence on use behavior. The same is also found in Wut's research (Wut et al., 2022). This is reasonable considering that during the COVID-19 period, the PeduliLindungi application is still considered a new phenomenon which then causes a perceived lack of facilities. For example, the knowledge and abilities that are still lacking to use the application, the lack of guidelines for using the application, and the lack of experts who can explain if users have difficulties when using the PeduliLindungi application. As a result, until users start to feel that the facilitating condition is getting better, the PeduliLindungi application seems to have obstacles to widespread adoption. Users who have difficulty using new technologies find it challenging to do so (Walczuch et al., 2007), making it harder for them to experience the advantages of the new technology. The use of the PeduliLindungi application during the COVID-19 pandemic owing to lack of assistance results in not changing use behavior, and these results provide a new understanding that facilitating conditions do not affect use behavior.

The role of gender moderation, age, and education to adopt the PeduliLindungi application as reported in Table 5 shows that no specific pathways were found that significantly affected them. Although the UTAUT construct affects both men and women, ages and levels of education variedly, it was not found that the three moderator variables moderated the UTAUT construct significantly.

An expanded model incorporating IPMA analysis and moderator factors has been validated and proven to explain Utilize Behavior in the adoption of the PeduliLindungi application, shedding light on how people used technology during the COVID-19 pandemic. The findings demonstrate that behavioral intention to use the PeduliLindungi application is influenced by performance expectation and effort expectancy, which aligns with previous research indicating that a positive attitude towards the application leads to increased intention to use it (Zeebaree et al., 2022).

Furthermore, the study reveals the impact of behavioral intention on use behavior, emphasizing the role of factors such as online spiritual meets (OSM), trust, perceived ease of use, and perceived enjoyment in influencing use behavior (Katoch & Rana, 2023; Hooda et al., 2022; Bai & Guo, 2022). This highlights the complex nature of technology adoption during the COVID-19 pandemic, where perceived benefits, usability, and concerns regarding contracting the disease play significant roles (Al-Maroof et al., 2020).

In addition, the study findings indicate that facilitating conditions, such as knowledge, guidelines, and expert support for using the PeduliLindungi application, do not have a significant influence on use behavior. This aligns with previous research findings (Wut et al., 2022) and can be attributed to the perceived lack of facilities and assistance during the initial stages of adopting a new technology like the PeduliLindungi application. Users may face challenges in utilizing the application and may not experience its advantages fully. These findings contribute to a deeper understanding that facilitating conditions do not directly affect use behavior in the context of the PeduliLindungi application.

The study also explores the role of gender, age, and education as moderator variables. However, the results reported in Table 5 indicate no significant pathways specific to these variables, suggesting that they do not significantly moderate the UTAUT constructs in this study. Although the UTAUT constructs influence both genders, various age groups, and educational levels, additional factors may contribute to the adoption of the PeduliLindungi application.

Overall, these insights provide valuable contributions to our understanding of the factors influencing the adoption of the PeduliLindungi application during the COVID-19 pandemic. The study underscores the importance of performance expectation, effort expectancy, and other relevant factors

in shaping behavioral intention and use behavior. Future research can further explore other factors and potential moderating effects to enhance our understanding of technology adoption in similar contexts.

In addition to the discussed factors, it is essential to address the concerns regarding data leakage and protection, as well as the issue of the behavior being compelled due to government requirements for using the PeduliLindungi application.

Data leakage and protection are significant considerations in the use of applications like PeduliLindungi, particularly when handling personal and sensitive information. While the present study primarily focuses on user acceptance and adoption, it is crucial to acknowledge the potential concerns surrounding data privacy and security. Future research could delve into these aspects to understand how users perceive and address data protection issues associated with the application. This would provide valuable insights into users' trust and confidence in the application, influencing their adoption and use behavior.

Furthermore, the government's role in mandating the use of the PeduliLindungi application introduces a unique dynamic. The requirement to use the application may lead to a sense of compulsion among individuals, potentially influencing their attitudes and behaviors towards adoption. It is important to consider the impact of this external factor on user acceptance and the challenges it may pose in fostering voluntary adoption. Understanding how individuals navigate this forced behavior and perceive the balance between public health concerns and personal choice can provide valuable insights into the nuances of technology adoption during unprecedented circumstances.

Addressing the issues of data leakage and protection, as well as the impact of government requirements on user behavior, would enhance the comprehensiveness of the study and provide a deeper understanding of the complexities surrounding the adoption of the PeduliLindungi application. By considering these aspects, researchers can gain insights into the interplay between user acceptance, data privacy, government mandates, and individual autonomy, contributing to a more holistic understanding of technology adoption in the context of public health initiatives.

Policy Implications

The movement for evidence-based policy (EBP) aims to encourage in-depth research of service programs and policy options to raise the standard of decision-making (Head, 2010). Today policy capacity has evolved concerning science, technology, and innovation (STI) (Wu et al., 2018). Research findings that can be viewed as a useful and necessary input for policymakers in the development of policies and programs of the PeduliLindingi Application can be reviewed from the discussion of the following policy implications.

The IPMA results demonstrate that construct behavioral intention plays a role in influencing use behavior to a certain extent, with effort expectation playing a larger role than other constructs. As a result, as they are the most significant and perform on average, characteristics connected to effort expectancy can be maximized to improve use behavior. The government can extend the amount of effort by putting more effort into making programs simpler to use, comprehend, and learn (Istiqoh et al., 2023). This is demonstrated by the fact that many users of the application grumbled about how difficult it was to learn, understand, and use it in the beginning (Personal et al., 2022). The adoption of the PeduliLindungi application and behavioral intention can both be increased with the support of the appropriate method (Aminullah & Erman, 2021).In this study, the three variables, namely performance expectation, effort expectation, and social influence, had a positive effect on behavioral intention. As a result, those who perform well in this dimension are more likely to adopt and utilize high-tech goods and services. These results confirm earlier research and are consistent with it. Performance expectation illustrates the belief of individuals that the PeduliLindungi application will improve their performance, in the context of overcoming COVID-19 in Indonesia, this is related to many community activities will be associated with this application, for example when traveling out of the city, entering malls, taking planes, trains and other activities related to attendance in public places. Meanwhile, effort expectation refers to the fact that the more it can be learned, understood, and run well, the PeduliLindungi application will increase the tendency to use this application. Social Influence refers to the trust of users that using this application will improve their status because after all, this application should be an application that must be used by all Indonesians to overcome COVID-19.

The findings demonstrated that improving a user-friendly environment is still challenging during the COVID-19 pandemic. Giving new PeduliLindungi app users training and mentorship to show them how to use the app and highlight features that suit their needs is one way to address this issue.

Watching videos on social media platforms like YouTube, Instagram, Twitter, etc., reading how-to guides on the websites of mobile service providers, and using the PeduliLindungi website can all help with this. The PeduliLindungi program has been used more frequently because of the COVID-19 epidemic, which has raised the risk of hacking and data leakage. Security features like encryption, biometrics, and authentication should be considered because they offer customers security benefits. Because there are numerous instances of application user data leakage security is crucial for Indonesians, and mass service providers must keep enhancing their data security (Yoebrilianti et al., 2022).

Performance Expectation, effort expectation, and social influence are prerequisites for behavioral intention and ultimately affect use behavior to use the PeduliLindungi application during the COVID-19 pandemic. For the PeduliLindungi application to be successful for a long time, it must be compatible with COVID-19 requirements that demand social distance, usability, and convenience of use. Along with its sense of security and comfort, the advantages of the PeduliLindungi application's usability and ease of use should be highlighted.

Although in general, the differences in groups, namely gender, age, and education do not affect the path coefficient, some interesting findings will be discussed. From the results of gender analysis, the results of the study support previous research (Shahbaz et al., 2020). Men have a greater tendency in terms of performance expectation, effort expectancy, and facilitating conditions. This means that men have a higher tendency to trust that the PeduliLindungi application will improve their performance, it is also easier to run it and some conditions support the use of the application. Meanwhile, in terms of behavioral intention and social influence, women have a greater tendency than men. This indicates that women are more likely to stick with the PeduliLindungi app and continue using it. The difference caused by age is mainly reflected in the fact that adult users have a higher tendency to assess and utilize the PeduliLindungi application. It also confirms previous research (Wei et al., 2021). Meanwhile, in terms of education level, users with educational backgrounds tend to have a higher behavioral intention value than users with higher levels of education. This may be because users with lower education levels accept all the shortcomings of the PeduliLindungi application, they don't mind things that are still considered lacking, while users with higher education levels are more "demanding" of the PeduliLindungi application. The results of the study revealed that there are still many obstacles to the adoption of the PeduliLindungi application technology in Indonesia, convincing the public to be able to take advantage of the PeduliLindungi application in the context of overcoming COVID-19 requires collaboration from stakeholders (government, academics, media, community leaders).

In addition to the previous discussion, as the pandemic situation develops and gradually improves, it is important to consider the state of the PeduliLindungi application in the future. It is important to explore the prospects for the PeduliLindungi application going forward after the COVID-19 pandemic and its potential for transformation into a more integrated application that offers a wider range of health features.

The findings from this study provide valuable insights that can inform policy makers and program developers in shaping the future direction of applications. Specifically, this research emphasizes the importance of performance expectations, effort expectations, and social influence in driving behavioral intention and usage behavior. Therefore, efforts should be directed at maximizing these characteristics to improve usage behavior and encourage wider application adoption.

In the long term, it will be especially important for health applications to be successful and survive, applications must emphasize the advantages of security, convenience, and application usability will be very important in maintaining user engagement and adoption.

In conclusion, the findings of this study offer valuable insights for policy makers, academics, media, and community leaders in increasing the adoption and use of the PeduliLindungi application in the context of tackling COVID-19. By addressing issues such as user education, data security, and aligning with user expectations, stakeholders can collaborate to ensure the long-term success and effectiveness of applications in support of public health efforts.

D. CONCLUSION AND RECOMMENDATION

Conclusion

This research has been able to expand the understanding of the adoption of the PeduliLindungi application with the analysis of Important-Performance Map Analysis and Multi Group Analysis, but,

there are still some limitations. First, the R-value of square facilitating behavior is still unsatisfactory. The usage patterns of the PeduliLindungi application during the COVID-19 epidemic are influenced by a variety of additional factors. Other technology adoption models can be used in a future study to explain the enabling circumstances for use behavior..

This research has provided valuable insights into the adoption of the PeduliLindungi application through the analysis of Important-Performance Map Analysis and Multi Group Analysis. However, it is important to acknowledge the limitations of this study and consider potential areas for further research.

One limitation is the unsatisfactory R-square value for facilitating behavior. The usage patterns of the PeduliLindungi application during the COVID-19 pandemic are influenced by various additional factors that were not fully captured in this study. Exploring other technology adoption models in future research can help explain the enabling circumstances that impact use behavior more comprehensively.

Furthermore, there may be additional variables that were not included in this study but could have a significant impact on the adoption and utilization of the PeduliLindungi application. These variables could be related to user characteristics, technological advancements, or contextual factors. Future research can explore and identify these variables to provide a more comprehensive understanding of the adoption process and its influencing factors.

Recommendation

To better understand use behavior, more investigation is required to pinpoint the key components of the PeduliLindungi application that should be the subject of the study. Second, this study is only focused on Indonesian app users, a developing nation. Results will vary depending on how technologically advanced a nation is.

To enhance the management of the PeduliLindungi application or develop a new application to replace it, several improvements can be proposed.

Firstly, further investigation is needed to identify the specific components of the PeduliLindungi application that significantly influence use behavior. By pinpointing these key factors, the government can focus on improving and optimizing those aspects to enhance user experience and encourage greater adoption.

Additionally, it is important to recognize that this study solely focuses on Indonesian app users within a developing nation context. To gain a more comprehensive understanding, it is recommended to conduct similar research in different countries with varying levels of technological advancement. This will provide insights into how the adoption and utilization of similar applications may differ based on the technological landscape and user preferences in each country.

By considering these improvements, the government can better manage the existing PeduliLindungi application or develop a new application that addresses the specific needs and preferences of the users. This will contribute to more effective and efficient technology adoption strategies and ultimately improve public health measures and safety during challenging times such as the COVID-19 pandemic.

REFERENCE

Akar, E., & Mardikyan, S. (2014). Analyzing factors affecting users ' behavior intention to use social media : Twitter. *International Journal of Business and Social Science*, *5*(11), 85–95.

Akbar, G. G., Kania, I., Ulumudin, A., Anggadwita, G., Harmanto, L. S., & Alamanda, D. T. (2019). Innovation in the Public Sector: The effectiveness of "LAPOR!" as one of the Smart City Programs in Bandung. *Proceedings of the International Symposium on Social Sciences, Education, and Humanities (ISSEH 2018)*. https://doi.org/10.2991/isseh-18.2019.69

Al-Maroof, R. S., Salloum, S. A., Hassanien, A. E., & Shaalan, K. (2020). Fear from COVID-19 and technology adoption: the impact of Google Meet during Coronavirus pandemic. *Interactive Learning Environments*, 1–16. https://doi.org/10.1080/10494820.2020.1830121

Albanna, H., Alalwan, A. A., & Al-Emran, M. (2022). An integrated model for using social media applications in non-profit organizations. *International Journal of Information Management*, *63*,

102452. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2021.102452
Allah Pitchay, A., Ganesan, Y., Zulkifli, N. S., & Khaliq, A. (2022). Determinants of customers' intention to use online food delivery application through smartphone in Malaysia. *British Food Journal*, *124*(3), 732–753. https://doi.org/10.1108/BFJ-01-2021-0075
Aminullah, E., & Erman, E. (2021). Policy innovation and emergence of innovative health technology: The system dynamics modelling of early COVID-19 handling in Indonesia. *Technology in Society*, *66*(July), 101682. https://doi.org/10.1016/j.techsoc.2021.101682
Andone, I., Blaszkiewicz, K., Eibes, M., Trendafilov, B., Markowetz, A., & Montag, C. (2016). How age and gender affect smartphone usage. *UbiComp 2016 Adjunct - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, *September*, 9–12. https://doi.org/10.1145/2968219.2971451
Bai, B., & Guo, Z. (2022). Understanding Users' Continuance Usage Behavior Towards Digital Health Information System Driven by the Digital Revolution Under COVID-19 Context: An Extended UTAUT Model. *Psychology Research and Behavior Management*, *Volume 15*(September), 2831–2842. https://doi.org/10.2147/prbm.s364275
Carranza, R., Díaz, E., Martín-Consuegra, D., & Fernández-Ferrín, P. (2020). PLS–SEM in business promotion strategies. A multigroup analysis of mobile coupon users using MICOM. *Industrial Management & Data Systems*, *120*(12), 2349–2374. https://doi.org/10.1108/IMDS-12-2019-0726
Chin, W. W., Peterson, R. A., & Brown, S. P. (2008). Structural Equation Modeling in Marketing: Some Practical Reminders. *Journal of Marketing Theory and Practice*, *16*(4), 287–298. https://doi.org/10.2753/MTP1069-6679160402
Eutsler, L. (2018). Parents' mobile technology adoption influences on elementary children's use. *The International Journal of Information and Learning Technology*, *35*(1), 29–42. https://doi.org/10.1108/IJILT-05-2017-0035
Ferreira, D., Dey, A. K., & Kostakos, V. (2011). *Understanding Human-Smartphone Concerns: A Study of Battery Life BT - Pervasive Computing* (K. Lyons, J. Hightower, & E. M. Huang (eds.); pp. 19–33). Springer Berlin Heidelberg.
Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
Head, B. W. (2010). Reconsidering evidence-based policy: Key issues and challenges. *Policy and Society*, *29*(2), 77–94. https://doi.org/https://doi.org/10.1016/j.polsoc.2010.03.001
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
Herdiana, D. (2021). Aplikasi PeduliLindungi : Perlindungan Masyarakat Dalam Mengakses Fasilitas Publik Di Masa Pemberlakuan Kebijakan PPKM. *Jurnal Inovasi Penelitian*, *2*(6), 1685–1694. https://doi.org/https://doi.org/10.47492/jip.v2i6.959
Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M., & Dwivedi, Y. K. (2022). The effects of trust on behavioral intention and use behavior within e-government contexts. *International Journal of Information Management*, *67*, 102553. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2022.102553
Istiqoh, A. E., Nurmandi, A., Muallidin, I., Loilatu, M. J., & Kurniawan, D. (2023). *The Successful Use of the PeduliLindungi Application in Handling COVID-19 (Indonesian Case Study) BT - Proceedings of Seventh International Congress on Information and Communication Technology* (X.-S. Yang, S. Sherratt, N. Dey, & A. Joshi (eds.); pp. 353–363). Springer Nature Singapore.
Katoch, R., & Rana, A. (2023). Online spiritual meets (OSMs) and user behavior – A divine application of technology during COVID-19. *Computers in Human Behavior*, *139*, 107514. https://doi.org/https://doi.org/10.1016/j.chb.2022.107514
Kock, N. (2014). One-tailed or two-tailed P values in PLS-SEM ? One-tailed or two-tailed P values in PLS-SEM ? ScriptWarp Systems . *International Journal of E-Collaboration*, *11*(December), 1–7. https://doi.org/10.13140/2.1.3788.1929
Liu, L., & Miguel-Cruz, A. (2022). Technology adoption and diffusion in healthcare at onset of COVID-19 and beyond. *Healthcare Management Forum*, *35*(3), 161–167.

https://doi.org/10.1177/08404704211058842
Miranda Difini, G., Martins, M. G., & Barbosa, J. L. V. (2022). A Movement Analysis Application Using Human Pose Estimation and Action Correction. *Proceedings of the Brazilian Symposium on Multimedia and the Web*, 359–367. https://doi.org/10.1145/3539637.3557931
Putri, C. E., & Hamzah, R. E. (2021). APLIKASI PEDULILINDUNGI MITIGASI BENCANA COVID-19 DI INDONESIA. *PUSTAKA KOMUNIKASI*, *4*(1), 66–78.
Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results. *Industrial Management & Data Systems*, *116*(9), 1865–1886. https://doi.org/10.1108/IMDS-10-2015-0449
Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Arshad, M. R. (2020). Moderating Effects of Gender and Resistance to Change on the Adoption of Big Data Analytics in Healthcare. *Complexity*, *2020*. https://doi.org/10.1155/2020/2173765
Srinivasa Rao, A. S. R., & Vazquez, J. A. (2020). Identification of COVID-19 can be quicker through artificial intelligence framework using a mobile phone-based survey when cities and towns are under quarantine. *Infection Control and Hospital Epidemiology*, *41*(7), 826–830. https://doi.org/10.1017/ice.2020.61
Venkatesh, V., & Smith, R. H. (2003). User Acceptance of Information Technology: Toward a Unified View. *Inorganic Chemistry Communications*, *27*(3). https://doi.org/10.2307/30036540
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376. https://doi.org/10.17705/1jais.00428
Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Information & Management*, *44*(2), 206–215. https://doi.org/https://doi.org/10.1016/j.im.2006.12.005
Wei, M. F., Luh, Y. H., Huang, Y. H., & Chang, Y. C. (2021). Young generation's mobile payment adoption behavior: Analysis based on an extended utaut model. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(4), 1–20. https://doi.org/10.3390/jtaer16040037
Wu, X., Ramesh, M., & Howlett, M. (2018). Policy Capacity and Governance. *Policy Capacity and Governance*, 1–25. https://doi.org/10.1007/978-3-319-54675-9
Wut, T. M., Lee, S. W., & Xu, J. (. (2022). How do Facilitating Conditions Influence Student-to-Student Interaction within an Online Learning Platform? A New Typology of the Serial Mediation Model. In *Education Sciences* (Vol. 12, Issue 5). https://doi.org/10.3390/educsci12050337
Yoebrilianti, A., Nurhyani, N., & Ikhsan, K. (2022). M-Payment and Covid-19: Understanding the Determinants of Consumers Adopting and Recommending Digital Payment System. *Jurnal Manajemen Dan Kewirausahaan*, *10*(1), 58–70. https://doi.org/10.26905/jmdk.v10i1.6614
Zeebaree, M., Agoyi, M., & Aqel, M. (2022). Sustainable Adoption of E-Government from the UTAUT Perspective. In *Sustainability* (Vol. 14, Issue 9). https://doi.org/10.3390/su14095370