Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 19(2), September 2023, 262–282

FACTORS INFLUENCING ACCEPTANCE OF INDONESIAN CONTACT TRACING APP: DEVELOPMENT OF THE TECHNOLOGY ACCEPTANCE MODEL

Rifki Nur Priyansyah
Padjadjaran University
Indonesia
ORCID 0000-0003-4943-251X

Ikhsan Fuady
Padjadjaran University
Indonesia
ORCID 0000-0002-8783-2867

Benazir Bona Pratamawaty
Padjadjaran University
Indonesia
ORCID 0000-0002-8641-3986

Abstract: *Contact tracing apps for the COVID-19 have been broadly developed worldwide and Indonesia is no exception. The Indonesian application is called PeduliLindungi. This study aimed to provide a comprehensive understading of the public's intention to use such applications by incorporating trust, trust in government, privacy concerns, and social influence variables as an extension to the technology acceptance model (TAM). A questionnaire was distributed online through social media to attain 371 participants among Indonesian inhabitants based on the convenience sampling method. Descriptive analysis and covariance-based structural equation modeling were used to analyze the data. The results indicated that intention was predicted well by trust, attitude, and social influence. Furthermore, trust in government played a role in predicting the application's trustworthiness. The government and decision-makers should consider this observation in promoting the PeduliLindungi application, as it could increase its effectiveness.*

Keywords: *COVID-19, Indonesia, technology acceptance model, mHealth, contact tracing app, structural equation modeling.*

DOI: https://doi.org/10.14254/1795-6889.2023.19-2.7

INTRODUCTION

Health technologies have played an influential role in preventing and controlling the spread of Covid-19 (Ye, 2020) and supporting healthcare organizations in making important decisions (Vaishya et al., 2020). For example, artificial intelligence has contributed to discovering COVID-19 clusters (Vaishya et al., 2020), while mobile technology has provided an easier way to spread awareness about virus transmission with its ability to map the spread of COVID-19 (Verma & Mishra, 2020). In particular, mobile health apps have become increasingly necessary, as they help to organize patient-generated health data crucial for tracing and tracking the diffusion of the virus (Ye, 2020). Due to such critical role of mobile health apps, numerous countries have been developing and publishing them officially (Criddle & Kelion, 2020). However, any application's success in suppressing the number of cases depends on the number of its users (Altmann et al., 2020).

In Singapore, the mobile application uses short-distance Bluetooth signals that automatically detect individuals close in proximity; through this, the government can detect the individuals an infected person has contacted (Whitelaw et al., 2020). In Switzerland, SwissCovid – their application's official name – adopted the decentralized privacy-preserving proximity tracing (DP-3T) protocol; this application has been downloaded by almost half the population (von Wyl et al., 2021). Similar to SwissCovid, the NZ Covid Tracer App developed by New Zealand's Ministry of Health has been downloaded by more than 2 million people, although less than 400 people use it daily (Tretiakov & Hunter, 2021). In Germany, the number of installed applications accounted for 20% of the population (Blom et al., 2021).

Along with optimizing the vaccination program, the Indonesian government developed a Covid-19 tracing application called PeduliLindungi to help control the spread of COVID-19. The application was officially launched in April 2020. Using the application, users can obtain information about the risk level in their area. On the other hand, the app assists the government in tracing and tracking new cases (Lin et al., 2020). On July 1, 2021, the Indonesian Ministry of Health published new developments in the application, enabling users to obtain digital vaccine certificates. They also mandated the public to scan QR Codes provided in public places with the built-in scanner in the apps whenever they enter them. These developments helped in intensifying tracking and contact tracing. As a result, proper login through the apps has become the main requirement for entering public places such as Ancol Beach Park and supermarkets.

Some studies have been conducted to investigate the role of the application in combating the transmission of COVID-19 in Indonesia (Kurniawati et al., 2020; Suryaatmadja & Maulani, 2020). Moreover, one study used the technology acceptance model (TAM) approach–using the first model introduced by Davis (1989)–to measure public acceptance of the application (Kurniawati et al., 2020). Another study extended the TAM further by incorporating two variables: privacy concerns and trust (Velicia-Martin et al., 2021). Despite not utilizing the TAM, another study has examined the role of trust, trust in government, and social influence in public acceptance of Covid-19 tracing apps (Oldeweme et al., 2021). In the many developments of the TAM by many researchers (Lee et al., 2003), we found that no researcher has studied it more deeply by incorporating other seemingly important variables (trust, trust in government, privacy concerns, and social influence) simultaneously from the TAM perspective. Therefore, this study endeavors to address the existing research gap through the examination of the influence of perceived usefulness, perceived ease of use, attitude towards the app, trust, trust in government, privacy concern, and social influence on the apps' adoption. In the context of PeduliLindungi, we included the new application updates (integration with 15 other apps, QR-Code scanner, etc.) to capture the ground reality better (in previous research projects about the app, these updates were not present yet). Thus, we hope the findings of this study can support the government and its stakeholders in their need to enforce application use further (Antara, 2021).

The Core Constructs of the TAM

Davis (1989) proposed that user acceptance of technology depended on its perceived usefulness and ease of use. Perceived usefulness is the level of an individual's belief that the technology can enhance their job performance. As for perceived ease of use, it's the level of an individual's belief that the technology does not require much effort to use (Davis, 1989). Both constructs influence the individual's attitude towards acceptance behavior (Aggelidis & Chatzoglou, 2009; Cheung & Vogel, 2013; Kim & Park, 2012; Lim & Ting, 2012). Attitude is described as the level of an individual's evaluation of whether a behavior is deemed advantageous or not (Ajzen, 1991). Perceived ease of use also influences perceived usefulness (Aggelidis & Chatzoglou, 2009; Cheung & Vogel, 2013; Ha & Stoel, 2008; J. Joo & Sang, 2013; Y. J. Joo et al., 2018; Kim & Park, 2012; Lim & Ting, 2012; Venkatesh & Davis, 2000). Afterward, the attitude leads to the intention to perform the behavior (or motivation [Ajzen, 1991]) and ends with the performing of the actual behavior (Legrisa et al., 2001).

H1: Perceived usefulness positively influences attitude towards PeduliLindungi Application.

H2: Perceived ease of use positively influences perceived usefulness.

H3: Perceived ease of use positively influences attitude towards PeduliLindungi Application.

Although TAM did not originate from a health-related context, a study (Holden & Karsh, 2010) found dozens of health care studies using and mentioning the model. However, these studies didn't focus on Covid-19 tracing apps but other technologies such as telemedicine, internet-based health applications, and mobile health care systems. Although, studies that utilized the TAM to investigate the adoption of COVID-19 contact tracing apps were also found (Kurniawati et al., 2020; Velicia-Martin et al., 2021; Walrave et al., 2021).

Ancillary Constructs of the TAM

TAM's objective is to examine the effect of external variables on internal beliefs, attitudes, and intentions toward accepting a technology (Legrisa et al., 2001). In telehealth, attitude is defined as positive or negative feelings toward telehealth service usage (An et al., 2021). Therefore, in this case, attitude is defined as the positive or negative feelings toward using a COVID-19 tracing app. Derived from the TAM, attitude affects intention to use (Aggelidis & Chatzoglou, 2009; Davis, 1989; Ha & Stoel, 2008; P. J. Hu et al., 1999; Kim & Park, 2012). Davis (1989) also found an unmediated relationship between perceived usefulness and intention. Other studies have proved this relationship in the context of health technologies (Aggelidis & Chatzoglou, 2009; P. J. Hu et al., 1999; Kim & Park, 2012), fitness application (Beldad & Hegner, 2018), and even Covid-19 contact tracing applications (Tomczyk et al., 2021).

H4: Attitude towards PeduliLindungi positively influences intention to use.

H5: Perceived usefulness positively influences intention to use.

Several studies found a positive relationship between trust and intention to use (Kamal et al., 2020; Oldeweme et al., 2021; Velicia-Martin et al., 2021). Other studies are more specific by incorporating the "trust in government" variable –which also affects trust in general (Oldeweme et al., 2021; von Wyl et al., 2021). Although, we also found a study (Beldad & Hegner, 2018; Tretiakov & Hunter, 2021) that discovered an insignificant relationship between trust and intention. In the technology acceptance context, trust is faith in a technology's ability to provide good services (Kamal et al., 2020). Additionally, a study on e-shopping revealed that trust also significantly affects perceived usefulness and attitude (Ha & Stoel, 2008).

H6: Trust in PeduliLindungi positively influences intention to use.

H7: Trust in government positively influences trust in PeduliLindungi.

H8: Trust in PeduliLindungi positively influences perceived usefulness.

H9: Trust in PeduliLindungi positively influences attitude toward using.

One study argued that trust in government correlates with the perception of privacy security (von Wyl et al., 2021). It's foreseeable since the policymakers are responsible for designing privacy regulations (Trang et al., 2020). Privacy concerns have become a primary barrier to using Covid-19 tracing apps (Altmann et al., 2020; von Wyl et al., 2021). It has been described as an individual's concern about the leak of personal information when using a Covid-19 tracing application (Kamal et al., 2020). A study has confirmed a negative relationship between privacy concerns and attitude (An et al., 2021). However, another study didn't find any relationship between the two (Tretiakov & Hunter, 2021). Although a study discovered a direct effect on intention (Walrave et al., 2021), two other studies did not find it significant (Kamal et al., 2020; Velicia-Martin et al., 2021).

H10: Privacy concern within PeduliLindungi negatively influences trust in government.

H11: Privacy concern within PeduliLindungi negatively influences attitude toward using.

Furthermore, a study found that social influence is positively associated with the usage number of COVID-19 tracing applications (Seto et al., 2021). A study (Oldeweme et al., 2021) has discovered an effect of social influence on trust and intention (Kamal et al., 2020), while another study found a connection between social influence and perceived usefulness (Aggelidis & Chatzoglou, 2009). In their extension of the TAM, Venkatesh and Davis (2000) mentioned a connection between social influence with intention and perceived usefulness. Social influence (the extent to which significant others are perceived as encouraging the use of the app) provides information by which an individual can reduce uncertainty about the application through interactions and the environment, including workplaces that require it (Tretiakov & Hunter, 2021). In addition, people tend to utilize technology if their families or relatives advocate it (Kamal et al., 2020). One study has confirmed all the above directions (Beldad & Hegner, 2018).

H12: Social influence positively influences perceived usefulness.

H13: Social influence positively influences trust in PeduliLindungi.

H14: Social influence positively influences intention to use.

Figure 1 describes the proposed research model based on the hypotheses. This study attempts to find a more comprehensive picture of the drivers of acceptance of the PeduliLindungi application by incorporating privacy, trust, trust in government, and social influence variables. The results could then aid the Indonesian government and its stakeholders in optimizing the app's further developments.

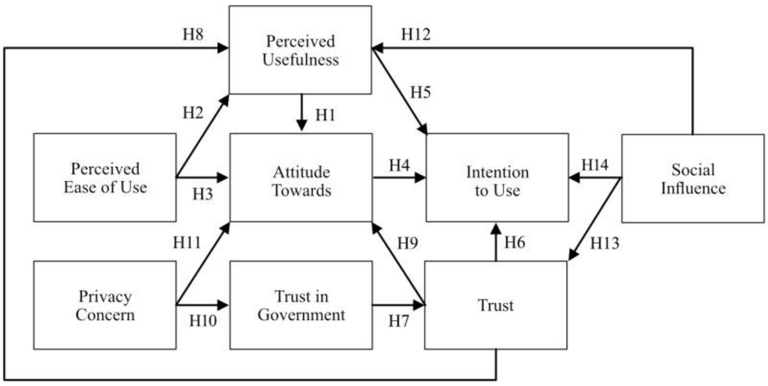

Figure 1. Proposed Research Model.

METHODS

Procedure and Data Collection

A minimum sample size was determined based on Soper's A-priori Sample Size Calculator for Structural Equation Models (2023) which generated 177 samples (effect size of .30 (Doulani, 2018; Feng et al., 2021); statistical power level of .80 (Wolf et al., 2013); alpha level of .05). It is also recommended to gather more than 200 samples in conducting structural equation modeling (Kyriazos, 2018). Therefore, we gathered 402 participants to fill out a questionnaire. The survey was conducted from October 26, 2021, to November 12, 2021. Because of the similarity of all answers and some missing answers, 31 participants were excluded. The link to the questionnaire was shared through social media using the convenience sampling method. Before answering the questions, the participants were asked for informed consent adopted from the Research Ethics Committee of Padjadjaran University (KEP Unpad). In measuring the constructs, 34 items were compiled.

Measurement

We measured the original TAM variables with a questionnaire developed by Tomczyk et al. (2021) as the basis. As for intention, we used three items (e.g., "I intend to use this app in the future.") built from a model developed by Velicia-Martin et al. (2021) to measure it. Perceived usefulness was assessed using six items (e.g., "PeduliLindungi can improve the tracing of infection chains."). As for perceived ease of use, four items (e.g., "The features of PeduliLindungi are clear and easy to operate.") were used. For the additional variables: trust (4 items), trust in government (4 items), and privacy concerns (5 items), we adopted the items from a study by Oldeweme et al. (2021). Finally, social influence was measured using four items (e.g., "Other people expect me to use such an app.") developed by Tomczyk et al. (2021). All variables were assessed based on a 5-point Likert scale from "strongly disagree" to "strongly agree," except for attitude, which was assessed on a 5-point semantic differential (e.g., “bad” to “good”). Each item used in the construct is presented in Appendix.

Explanatory factor analysis (EFA) was conducted to ascertain that the questions measured each variable separately. We excluded items with poor factor loadings (<.40) considering that items with loadings under .40 are not good enough to represent the measured variable significantly as it opens the possibility of representing other variable (Maskey, 2018); high loadings indicate good correlations between the items and its measured variabels (Watkins, 2018). We conducted confirmatory factor analysis (CFA) afterward. The reliability was assessed by Cronbach’s alpha, in which each variable is required to fall between the interval of .70–.95 (Tavakol & Dennick, 2011).

Data Analysis

Descriptive analysis was carried out to discover the means and standard deviations of each item and describe the participants’ characteristics. We also defined the mean intention across the groups. Before the hypotheses test, we assessed the correlation and fit of the model by measuring the ratio of chi-square (χ^2) to degrees of freedom (df), comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of affirmation (RMSEA). Then we used JASP software to evaluate the research hypotheses based on the lavaan package. Finally, we utilized maximum likelihood estimation to test the path regression using the Satorra-Bentler method because it has been reported to be more accurate than other methods (Marcoulides et al., 2020).

RESULTS

Participants Characteristics

After exclusion, 371 participants were included in this study. Table 1 presents the demographic information. The sex distributions of the participants were nearly equal. Regarding age groups, the participants were well distributed except for those aged 55 until 70, which amounts to just 19 (nearly 5%). The data were centralized in Java with 328 participants. The remaining participants were distributed across six islands, with less than 10% of the participants for each island. Most participants (48.5%) hold a bachelor’s degree, and 66 have a master’s degree. Regarding occupations, most participants were employees or civil servants. In addition, we also collected health workers (2 participants), pensioners (2 participants), and an architect (1 participant).

Table 1. Characteristics of Participants.

Characteristics	Participant, n (%)	Mean Intention (SD)
Gender		
Female	173 (46.6)	3.726 (.885)
Male	198 (53.4)	3.645 (1.041)
Age		
18 – 24 years old	97 (26.15)	3.814 (.919)
25 – 34 years old	88 (23.72)	3.496 (.964)
35 – 44 years old	92 (24.80)	3.402 (.993)
45 – 54 years old	75 (20.22)	4.009 (.894)
Above 54 years old	19 (5.12)	3.947 (.964)
Domicile		
Non Java	43 (11.6)	3.969 (.908)
Sumatera	26 (7.0)	
Riau Islands	6 (1.6)	
Kalimantan	5 (1.3)	
Lesser Sunda Islands	1 (.3)	
Sulawesi	4 (1.1)	
Maluku Islands	1 (0.3)	
Java	328 (88.4)	3.645 (.974)
Educational Level		
High school or lower	97 (26.2)	3.718 (1.021)
Associate’s degree	28 (7.5)	3.369 (.970)
Bachelor’s degree	180 (48.5)	3.565 (.894)
Master’s degree	60 (16.2)	4.111 (.966)
Doctoral degree	6 (1.6)	3.833 (1.329)
Occupation		
Housewife	32 (8.6)	3.365 (.852)
Civil servant	97 (26.1)	4.055 (.940)
Employee	121 (32.6)	3.477 (.923)
Student	66 (17.8)	3.995 (.832)
Entrepreneur	29 (7.8)	3.379 (1.064)
Teacher	11 (3)	3.273 (1.104)
Others	15 (4)	3.133 (.966)

The intention to use the application exceeded 3.00 across all groups. As the overall median of participants’ intention was 4.00, a score above that was considered as high intention. Low intention was presented by a score under 2.00 while medium intention was presented by a score of 2-4, as explained by Coyer with her colleagues (2019). We did not find any low intention between the groups because the minimum mean was only 3.133. Therefore, all participants can at least be classified as having a moderate intention, according to Table 2. For gender groups, we detected similarity levels of intention between females and males, contradicted a previous study (Grill et al., 2021). Interestingly, people aged above 54 years still have a high intention to use PeduliLindungi (which counts as new technology). This finding aligns with a survey (Vogels, 2019) conducted in the US that found a significant escalation in technology adoption among “baby boomers.” The survey also found that nearly seven out of ten baby boomers own a smartphone (Vogels, 2019). In particular, positive evaluations regarding a contact tracing app were found higher in older people in Germany (Grill et al., 2021). Thus, age is not a barrier to the adoption of new technologies, in contrast to prior studies (Ross, 2021; Walrave et al., 2020). Islands outside Java were reported to nearly have a high intention with score of 3.969. Location has been determined to be a significant factor in app acceptibility (Abuhammad et al., 2020; Grill et al., 2021). The highest mean was for those who had completed master’s degrees, reaching 4.111. Students and doctors also almost had a high intention to use the app. Regarding occupation, the mean intention of teachers (including lecturers) was moderate, although it reached only 3.273. This finding has to be considered because teachers and similar professions have regular contact with many people. Students and civil servants had strong intentions. This finding confirmed that civil servants are loyal to the government.

Table 2. Classification Criteria.

Classification	Interval
Low	<2
Moderate	2-4
High	>4

Measurement Model

Explanatory factor analysis was performed. We used the maximum likelihood factor analytic method as it's more suitable for the structural equation modeling approach (Howard, 2016) rotated by the oblique (oblimin) method. Following the test, we excluded two items under privacy concerns and 1 item under trust because of poor factor loadings (they did not exceed .40) (Watkins, 2018). After that, confirmatory factor analysis from the lavaan package (Rosseel, 2012) reported high factor loadings which exceeded .60 for each item (Arifin & Yusoff, 2016). Regarding the AVE, our items had good convergent validity since the value exceeded .50 (Sakib et al., 2022). The model fit was also sufficient (see Table 3) in terms of $\chi 2$ / df ratio (<3) (Aggelidis & Chatzoglou, 2009; Oldeweme et al., 2021), CFI (>.90), RMSEA (<.080), and TLI (>.90) (Sakib et al., 2022),

Table 3. Model Fit Criteria.

Model	$\chi 2$/df	CFI	TLI	RMSEA
CFA	912.56 / 405	.951	.944	.058
Path Model	1157.03 / 417	.929	.921	.069

Note. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Affirmation. **Model:** CFA = Confirmatory Factor Analysis.

Cronbach's alpha and composite reliability were applied to test reliability. All constructs showed good results, with a value of more than .90 except for privacy concerns and trust. In conclusion, the reliability of the constructs was adequate, exceeding .70 (Bujang et al., 2018) for Cronbach's alpha and .60 for composite reliability (Sakib et al., 2022). Table 4 shows the results of the measurement model.

Table 4. Validity and Reliability Score.

Construct and Item	Mean (SD)	EFA	CFA	AVE	CR	CA
Perceived usefulness (PU)	3.702 (.864)			.655	.919	.917
pu1	3.819 (1.001)	.484	.780			
pu2	3.358 (1.138)	.686	.809			
pu3	3.806 (.995)	.467	.720			
pu4	3.987 (.934)	.568	.834			
pu5	3.666 (1.035)	.829	.869			
pu6	3.577 (1.035)	.723	.835			
Perceived ease of use (PEASE)	4.019 (.825)			.728	.914	.910
pease1	3.871 (.997)	.708	.799			
pease2	3.962 (.932)	.788	.900			
pease3	4.038 (.915)	.968	.920			
pease4	4.208 (.871)	.783	.785			
Privacy concern (PRIVAT)	3.230 (.774)			.624	.830	.819
privat1	3.695 (.979)	.351	Excluded			
privat2	3.571 (1.140)	.613	.636			
privat3	2.757 (1.030)	.253	Excluded			
privat4	3.151 (1.077)	.834	.835			
privat5	2.973 (1.110)	.839	.877			
Attitude towards (ATT)	3.635 (.825)			.742	.920	.919
att1	3.792 (.926)	.628	.893			
att2	3.348 (.936)	.477	.800			
att3	3.598 (.881)	.678	.833			
att4	3.803 (.934)	.793	.915			
Trust in government (GOV)	3.498 (.922)			.788	.937	.936
gov1	3.499 (.996)	.849	.888			
gov2	3.515 (.979)	.864	.924			
gov3	3.496 (1.033)	.826	.843			
gov4	3.482 (1.020)	.901	.893			
Trust (TRU)	3.641 (.878)			.725	.888	.884
tru1	3.639 (1.067)	.471	.802			
tru2	3.566 (1.007)	.533	.883			
tru3	3.582 (.939)	.464	.868			
tru4	3.779 (.947)	.371	Excluded			
Social influence (SOCIAL)	3.678 (.871)			.747	.922	.919
sosial1	3.714 (.961)	.913	.893			
sosial2	3.650 (.965)	.827	.897			
sosial3	3.682 (.945)	.537	.759			
sosial4	3.674 (1.013)	.859	.900			
Intention to use (INTENT)	3.683 (.971)			.842	.941	.941
intent1	3.749 (1.008)	.795	.896			
intent2	3.682 (1.030)	.880	.938			
intent3	3.617 (1.042)	.796	.919			

Note. EFA = Explanatory Factor Analysis. CFA = Confirmatory Factor Analysis. AVE = Average Variance Extracted. CR = Composite Reliability. CA = Cronbach's aplha.

Hypotheses Testing

All constructs were reported to correlate ($p<.001$). Privacy concerns also was detected to negatively correlate with the other variables (see Table 5). However, users could possibily use the app despite concerning their privacy in order to prioritize their health (Nguyen et al., 2023), as found in Malaysia (Alshami et al., 2022). The proposed path model was reported to have an adequate fit considering the same cutoff as before, as summarized in Table 3. Therefore, all paths from the hypotheses were accepted except for H5 (β=.047; p=.514) and H12 (β=.097; p=.096).

Table 5. Correlation Matrix.

Constructs	pu	pease	att	tru	privat	social	gov	intent
pu	1.000							
pease	.622*	1.000						
att	.770*	.664*	1.000					
tru	.829*	.730*	.817*	1.000				
privat	-.375*	-.349*	-.455*	-.456*	1.000			
social	.631*	.599*	.703*	.652*	-.254*	1.000		
gov	.597*	.493*	.667*	.655*	-.304*	.549*	1.000	
intent	.677*	.615*	.767*	.725*	-.288*	.734*	.566*	1.000

Note. Pu = perceived usefulness. Pease = perceived ease of use. Att = attitude towards. Tru = trust. Privat = privacy concern. Social = social influence. Gov = trust in government. Intent = intention to use.
**p*<.001; Correlation coefficients are standardized.

Table 6 shows a positive effect of perceived ease of use (β =.170; p <.001) and trust (β =.664; p <.001) on perceived usefulness, but not for social influence (β=.097; p<.096), although the p-value did not exceed .10. Hence, only H2 and H8 were accepted. Attitude was significantly influenced by perceived usefulness (β=.206; p<.01), perceived ease of use (β=.150; p<.001), trust (β=.522; p<.001), and privacy concern (β=-.130; p<.01). Therefore, H1, H3, H9, and H11 were supported. Furthermore, intention had 3 out of 4 predictors, which we accepted. Perceived usefulness did not significantly affect intention (β=.047; p=.514) showing that the effect had to be mediated by attitude which is not only affected by perceived usefulness. Attitude (β=.329; p<.001), trust (β=.170; p<.05), and social influence (β=.380; p<.001) were found to have significant effects on intention. Thus, H4, H6, and H14 were supported.

Table 6. Hypothesis results.

Code	**Hypotheses**		**R^2**	**β^a (SE)**	***p* value**	**Evaluation of hypotheses**
	Predictor	Outcome				
H2	pease			.170 (.047)	<.001	Approved
H8	tru	pu	.656	.664 (.059)	<.001	Approved
H12	social			.097 (.049)	.096	**Rejected**
H10	privat	gov	.124	-.352 (.073)	<.001	Approved
H7	gov	tru	.541	.483 (.043)	<.001	Approved
H13	social			.506 (.045)	<.001	Approved
H1	pu			.206 (.077)	.005	Approved
H3	pease	att	.686	.150 (.043)	<.001	Approved
H9	tru			.522 (.073)	<.001	Approved
H11	privat			-.130 (.044)	.002	Approved

H4	att	intent	.636	.329 (.080)	<.001	Approved
H5	pu			.047 (.085)	.514	**Rejected**
H6	tru			.170 (.090)	.040	Approved
H14	social			.380 (.048)	<.001	Approved

Note. Pu = perceived usefulness. Pease = perceived ease of use. Att = attitude towards. Tru = trust. Privat = privacy concern. Social = social influence. Gov = trust in government. Intent = intention to use.
[a]Standardized path coeffecients.

The remaining hypotheses were also supported. Trust was significantly influenced by trust in government (β=.483; p<.001), which supported H7, and social influence (β=.506; p<.001), which supported H13. Lastly, we also found support for H10, as privacy concerns negatively impacted trust in government (β=-.352; p<.001). The results are also illustrated in Figure 2.

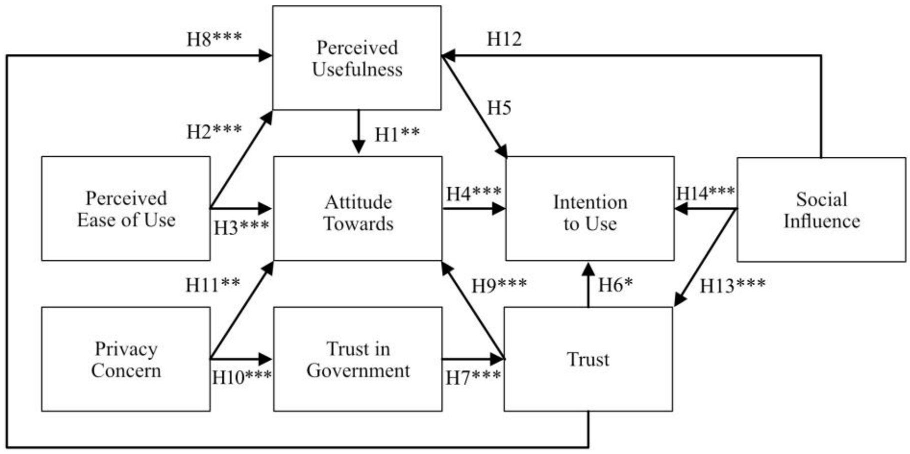

Figure 2. Research Model Results

Note. **p*<.05; ***p*<.01; ****p*<.001

DISCUSSION

Regarding the core variables of TAM, perceived usefulness had a more significant effect on predicting attitude than perceived ease of use. Interestingly, a previous study on the acceptance of COVID-19 contact tracing apps (Velicia-Martin et al., 2021) found that ease of being safe from virus transmission matters more to the respondents than the ease of using the app. Nevertheless, this previous study mentioned above found an effect of perceived usefulness on attitude, in contrast to a prior study (Kurniawati et al., 2020). Perceived usefulness was reported to have a more significant effect on intention than perceived ease of use. This finding corresponded with the results of a previous study (Velicia-Martin et al., 2021). Our results also reported a less influential role of attitude in predicting intention than prior studies (Kurniawati et al., 2020; Kwarteng et al., 2023; Velicia-Martin et al., 2021). Another hypothesis of genuine TAM was the connection between perceived ease of use and usefulness. Our results confirmed the findings of previous studies (Aggelidis & Chatzoglou, 2009; Cheung & Vogel, 2013; Ha & Stoel, 2008; J. Joo & Sang, 2013; Y. J. Joo et al., 2018; Lim & Ting, 2012; Venkatesh & Davis, 2000) which detected a significant effect. It explained that the ease of using the application (including the information and support the app could provide) could impact the public's perception of its ability to overcome infection risks.

Conversely, our results showed that perceived usefulness did not influence intention (to use), unlike attitude. Hence, the respondents who hold a higher evaluation of the application's usefulness do not necessarily have a greater intention to use the application. Despite contradicting previous studies (Aggelidis & Chatzoglou, 2009; Alshami et al., 2022; Kamal et al., 2020; Kim & Park, 2012; Kurniawati et al., 2020; Tomczyk et al., 2021; Velicia-Martin et al., 2021) and meta-analysis (Holden & Karsh, 2010), the results are the same with those from a study in the context of mobile learning (Park et al., 2012). They argued that the convenience of using the mobile device results in an indirect effect. Similarly, Indonesian perceptions of ease of use had the highest mean (M=4.019; SD=.825). In addition, public perceptions that the app can reduce COVID-19 transmissions did not predict the acceptance of the app in China (Kostka & Habich-Sobiegalla, 2022). Indonesia and China have the same policy regarding the obligation to use the app that could be a factor in the impact of perceived usefulness. According to our results, the public intention was affected more by other constructs like social influence and trust. Presumably, when people don't receive any influence from their surroundings, they will not use the application despite realizing its benefits.

Additionally, social influence played a crucial role since it affected trust and intention with the highest effect compared to other predictors. This result was in line with previous studies in the context of trust (Beldad & Hegner, 2018; Oldeweme et al., 2021) and intention as an outcome (Aggelidis & Chatzoglou, 2009; Alshami et al., 2022; Huang et al., 2022; Oldeweme et al., 2021). Therefore, the surrounding encouragement influences the public's willingness to use the application. Thus, when the app's use is not required in many public places, public acceptance of the app will also be lower (Nurita, 2021). The item about family influence was reported to have the highest mean, although the differences between the items were not significant. From this finding, we can also see that influence from people with no relationship with an individual still had an important role in predicting the individual's intention.

The role of social influence became more crucial because it also affected trust, which was the critical predictor of attitude. Trust in the application should be considered because it influences perceived usefulness, attitude (Ha & Stoel, 2008), and intention (Kamal et al., 2020; Oldeweme et al., 2021; Ukpabi et al., 2021; Velicia-Martin et al., 2021). The relationship between trust and perceived usefulness showed that the public hoped this application could solve the contagion of the virus. They also hoped that the application could aid the quarantine implementation. Furthermore, trust predicted attitude with the highest effect compared to others. By integrating trust and social influence, attitude still had a high impact on intention despite not exceeding social influence. Therefore, it showed that public trust and willingness to use the application depended on their social surroundings. Despite these findings, we detected no significant effect of social influence on intention, which differed from previous studies (Aggelidis & Chatzoglou, 2009; Beldad & Hegner, 2018). This discovery explained that social influence does not affect users' perception of the application's ability to lessen the infection risk and control the virus's diffusion.

Privacy concerns were found to negatively affect attitude, as in the previous study (An et al., 2021). This finding indicates that privacy has become a barrier to the acceptance of the application. A study in Singapore (Huang et al., 2022), Australia (Sun et al., 2021), China, Germany, and the United States (Kostka & Habich-Sobiegalla, 2022) also showed that people who are sure about their data security are more willing to use their contact-tracing app. However, we did not explore the direct effect of privacy on intention. Since some studies found no significant effect of privacy on intention (Abuhammad et al., 2020; Alshami et al., 2022; Kwarteng et al., 2023), the effect might be mediated by attitude, as our study showed. On the other hand, perceived usefulness and perceived ease of use did not strongly impact attitude compared to trust after incorporating them with privacy concerns. In addition, privacy concerns also affected trust in government, corresponding to a prior qualitative study (von Wyl et al., 2021). Privacy concern and trust in government had been detected to greatly detain the adoption of contact-tracing apps in several countries (Nurgalieva et al., 2021). Thus, the government should perfect the app's safety so that the adoption of the application can increase, as a prior study suggested (Kostka & Habich-Sobiegalla, 2022). Trust in government has also been confirmed to affect trust, in line with the prior works (Oldeweme et al., 2021; von Wyl et al., 2021). Accordingly, the public's trust in the government's online services and that they're keeping the public interest in mind can enhance their reliance on the application. Nevertheless, the involvement of privacy concerns in predicting attitude was not as crucial as others due to the effect size. But privacy concerns serve as a good predictor factor in predicting trust to government.

CONCLUSIONS

The PeduliLindungi as a COVID-19 contact tracing application is a vital tool in controlling the spread of the virus in Indonesia. The government has also made significant efforts to develop the app to make it easier to use. This study revealed the factors affecting the acceptance of the application in a broader picture. First, our results have confirmed the role of trust, social influence, and privacy in extending the technology acceptance model. Furthermore, the findings of this study also confirmed the necessity to include the trust in government variable in describing an app's acceptance. The trust in government variable becomes necessary because it affects trust in the application. Encouragement from families and other social aspects was also found as critical. To address the degradation of the number of application uses (Adyatama, 2021), the government and its stakeholders should strengthen public trust in the application or the government themselves. They also should drive social influence further by implementing communication programs and policies that will help influence the population's utilization of PeduliLindungi.

There are several limitations to this study. First, we conducted the study using the convenience sampling method, so it could not represent the total population. Hence, we recommend that future research projects employ probability sampling, particularly for traditional market populations, which were said to be not ready to use the application (Pebrianto, 2021). Second, this study did not examine the direct connection between privacy concerns and trust in government with intention. Nevertheless, these findings can help ascertain a relationship between those constructs. Third, other constructs such as self-efficacy, perceived convenience, exposure to health messages, perceived transmission risk, or perceived mandatory should be incorporated to examine their effect on intention or other constructs of the TAM.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

Theoretically, this study has examined the impact of trust, social influence, and privacy on the technology acceptance model. Moreover, our results confirmed the necessity of the trust in government variable in describing the acceptance of a Covid-19 tracing app. However, perceived usefulness did not significantly affect intention to use; thus, our findings rejected the principal theory. By integrating trust and social influence, attitude toward still had a substantial impact on intention to use despite not exceeding social influence. Astonishingly, perceived usefulness and ease of use did not strongly impact attitude compared to trust. Overall, the technology acceptance model has been validated in the context of the PeduliLindungi, which shows the model's effectiveness.

For practical purposes, the government and its stakeholders should strengthen the public's trust in the application or the government. Trust in government becomes necessary because it affects trust in the application. To attain such an objective, it is crucial for the government to exercise transparent and consistent communication (Zimmermann et al., 2021). Therefore, it is also recommended that healthcare professionals, media practitioners, and analysts be involved in promoting and campaigning for the adoption of the app. The combination of digital (such as social media) and traditional media (especially television) have to be arranged properly to reach wider audiences. Furthermore, privacy security, which leads to trust in government, must be strongly considered. Fortunately, the government sufficiently handled it when integrating PeduliLindungi with 15 other apps (Riana, 2021). Nevertheless, the government should perfect its safety to increase the adoption of the application.

Regarding social influence, campaigns, such as news, advertisement, socialization, etc., presumably can be considered an essential factor in public acceptance of PeduliLindungi. Besides that, encouragement to use the app from families and relatives is also crucial. App developers should amplify the protection of data users and simplify the user experience more. Although, the participants were recorded to report having a comfortable experience using the application, as shown by their questionnaire answers pointing to a high level of perceived ease of use.

REFERENCES

Abuhammad, S., Khabour, O. F., & Alzoubi, K. H. (2020). COVID-19 contact-tracing technology: acceptability and ethical issues of use. *Patient preference and adherence,* 1639-1647. https://doi.org/10.2147/PPA.S276183

Adyatama, E. (2021, December 13). *Serious Drop in PeduliLindungi Check-Ins Raises Concerns: Govt - News en.tempo.co*. TEMPO.CO. https://en.tempo.co/read/1538985/serious-drop-in-pedulilindungi-check-ins-raises-concerns-govt

Aggelidis, V. P., & Chatzoglou, P. D. (2009). Using a modified technology acceptance model in hospitals. *International Journal of Medical Informatics*, *78*(2), 115–126.

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies, 2*(4), 314-324. https://doi.org/10.1002/hbe2.195

Alshami, M., Abdulghafor, R., & Aborujilah, A. (2022). Extending the Unified Theory of Acceptance and Use of Technology for COVID-19 Contact Tracing Application by Malaysian Users. *Sustainability, 14*(11), 6811. https://doi.org/10.3390/su14116811

Altmann, S., Milsom, L., Zillessen, H., Blasone, R., Gerdon, F., Bach, R., Kreuter, F., Nosenzo, D., Toussaert, S., & Abeler, J. (2020). Acceptability of App-Based Contact Tracing for COVID-19: Cross-Country Survey Study. *JMIR MHealth and UHealth*, *8*(8), e19857. https://doi.org/10.2196/19857

An, M. H., You, S. C., Park, R. W., & Lee, S. (2021). Using an Extended Technology Acceptance Model to Understand the Factors Influencing Telehealth Utilization After Flattening the COVID-19 Curve in South Korea: Cross-sectional Survey Study. *JMIR Medical Informatics*, *9*(1), e25435. https://doi.org/10.2196/25435

Antara. (2021, December 14). *Luhut Calls for Massive Enforcement of PeduliLindungi COVID-19 App Use - News en.tempo.co*. TEMPO.CO. https://en.tempo.co/read/1539110/luhut-calls-for-massive-enforcement-of-pedulilindungi-covid-19-app-use

Arifin, W. N., & Yusoff, M. S. B. (2016). Confirmatory factor analysis of the Universiti Sains Malaysia emotional quotient inventory among medical students in Malaysia. *Sage Open, 6*(2). https://doi.org/10.1177/2158244016650240

Beldad, A. D., & Hegner, S. M. (2018). Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue using a Fitness App: A Structural Equation Modeling Approach. *International Journal of Human–Computer Interaction*, *34*(9), 882–893. https://doi.org/10.1080/10447318.2017.1403220

Blom, A. G., Wenz, A., Cornesse, C., Rettig, T., Fikel, M., Friedel, S., Möhring, K., Naumann, E., Reifenscheid, M., & Krieger, U. (2021). Barriers to the Large-Scale Adoption of a COVID-19 Contact Tracing App in Germany: Survey Study. *Journal of Medical Internet Research*, *23*(3), e23362. https://doi.org/10.2196/23362

Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for Cronbach's alpha test: a simple guide for researchers. *The Malaysian journal of medical sciences: MJMS, 25*(6), 85–99. https://doi.org/10.21315/mjms2018.25.6.9

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, *63*, 160–175.

Coyer, L., van Bilsen, W., Bil, J., Davidovich, U., Hoornenborg, E., Prins, M., & Matser, A. (2018). Pre-exposure prophylaxis among men who have sex with men in the Amsterdam Cohort Studies: Use, eligibility, and intention to use. *PLoS ONE, 13*(10), e0205663. https://doi.org/10.1371/journal.pone.0205663

Criddle, C., & Kelion, L. (2020, May 7). *Coronavirus contact-tracing: World split between two types of app - BBC News*. BBC News. https://www.bbc.com/news/technology-52355028

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340.

Doulani, A. (2018). An Assessment of Effective Factors in Technology Acceptance Model: A Meta-Analysis Study. *J. Sci. Res.*, *7*(3), 153-166. https://doi.org/10.5530/jscires.7.3.26

Feng, G. C., Su, X., Lin, Z., He, Y., Luo, N., & Zhang, Y. (2021). Determinants of technology acceptance: Two model-based meta-analytic reviews. *Journalism & Mass Communication Quarterly*, *98*(1), 83-104. https://doi.org/10.1177/1077699020952400

Grill, E., Eitze, S., De Bock, F., Dragano, N., Huebl, L., Schmich, P., Wieler, L. H., & Betsch, C. (2021). Sociodemographic characteristics determine download and use of a Corona contact tracing app in Germany—Results of the COSMO surveys. *PloS one*, *16*(9), e0256660. https://doi.org/10.1371/journal.pone.0256660

Ha, S., & Stoel, L. (2008). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2008.06.016

Huang, Z., Guo, H., Lim, H. Y. F., & Chow, A. (2022). Determinants of the acceptance and adoption of a digital contact tracing tool during the COVID-19 pandemic in Singapore. *Epidemiology & Infection*, 150, E54. https://doi.org/10.1017/S0950268822000401

Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Howard, M. C. (2016). A Review of Exploratory Factor Analysis Decisions and Overview of Current Practices: What We Are Doing and How Can We Improve? *International Journal of Human-Computer Interaction*, *32*(1), 51–62. https://doi.org/10.1080/10447318.2015.1087664

Joo, J., & Sang, Y. (2013). Exploring Koreans' Smartphone Usage: An Integrated Model of the Technology Acceptance Model and Uses and Gratifications theory. *Computers in Human Behavior*, *29*(2013), 2512–2518. https://doi.org/http://dx.doi.org/10.1016/j.chb.2013.06.002

Joo, Y. J., Park, S., & Lim, E. (2018). Factors Influencing Preservice Teachers' Intention to Use Technology: TPACK, Teacher Self-efficacy, and Technology Acceptance Model. *Educational Technology & Society*, *21*(3), 48–59.

Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society*, *60*, 101212. https://doi.org/10.1016/j.techsoc.2019.101212

Kim, J., & Park, H.-A. (2012). Development of a Health Information Technology Acceptance Model Using Consumers' Health Behavior Intention. *Journal of Medical Internet Research*, *14*(5), e133. https://doi.org/10.2196/jmir.2143

Kostka, G., & Habich-Sobiegalla, S. (2022). In times of crisis: Public perceptions toward COVID-19 contact tracing apps in China, Germany, and the United States. *New Media & Society*, *0*(0). https://doi.org/10.1177/14614448221083285

Kurniawati, Khadapi, M., Riana, D., Arfian, A., Rahmawati, E., & Heriyanto. (2020). Public Acceptance Of Pedulilindungi Application In The Acceleration Of Corona Virus (Covid-19) Handling. *Journal of Physics: Conference Series*, *1641*, 012026. https://doi.org/10.1088/1742-6596/1641/1/012026

Kwarteng, M. A., Ntsiful, A., Osakwe, C. N., & Ofori, K. S. (2023). Modeling the acceptance and resistance to use mobile contact tracing apps: a developing nation perspective. *Online Information Review*. https://doi.org/10.1108/OIR-10-2021-0533

Kyriazos, T. A. (2018). Applied psychometrics: sample size abd sample power considerations in factor analysis (EFA, CFA) and SEM in general. *Psychology*, *9*(8), 2207-2230. https://doi.org/10.4236/psych.2018.98126

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12*(50), 752–780.

Legrisa, P., Ingham, J., & Collerette, P. (2001). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management*, *40*, 191–204.

Lim, W. M., & Ting, D. H. (2012). E-shopping: an Analysis of the Technology Acceptance Model. *Modern Applied Science*, *6*(4), 49–61. https://doi.org/http://dx.doi.org/10.5539/mas.v6n4p49

Lin, P., Knockel, J., Poetranto, I., Tran, S., Lau, J., & Senf, A. (2020). *Unmasked II: An Analysis of Indonesia and the Philippines' Governmentlaunched COVID-19 Apps*.

Marcoulides, K. M., Foldnes, N., & Grønneberg, S. (2020). Assessing Model Fit in Structural Equation Modeling Using Appropriate Test Statistics. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(3), 369–379. https://doi.org/10.1080/10705511.2019.1647785

Maskey, R., Fei, J., & Nguyen, H. O. (2018). Use of exploratory factor analysis in maritime research. *The Asian journal of shipping and logistics, 34*(2), 91-111. https://doi.org/10.1016/j.ajsl.2018.06.006

Nguyen, T. T., Tran Hoang, M. T., & Phung, M. T. (2023). "To our health!" Perceived benefits offset privacy concerns in using national contact-tracing apps. *Library Hi Tech*, *41*(1), 174-191. https://doi.org/10.1108/LHT-12-2021-0461

Nurgalieva, L., Ryan, S., & Doherty, G. (2021). Attitudes towards covid-19 contact tracing apps: a cross-national survey. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3136649

Nurita, D. (2021, December 21). *PeduliLindungi Required in Public Spaces; Govt Preps Sanctions for Violators - News en.tempo.co*. TEMPO.CO. https://en.tempo.co/read/1541750/pedulilindungi-required-in-public-spacesgovt-preps-sanctions-for-violators

Oldeweme, A., Märtins, J., Westmattelmann, D., & Schewe, G. (2021). The Role of Transparency, Trust, and Social Influence on Uncertainty Reduction in Times of Pandemics: Empirical Study on the Adoption of COVID-19 Tracing Apps. *Journal of Medical Internet Research*, *23*(2), e25893. https://doi.org/10.2196/25893

Park, S. Y., Nam, M.-W., & Cha, S.-B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology*, *43*(4), 592–605. https://doi.org/10.1111/j.1467-8535.2011.01229.x

Pebrianto, F. (2021, September 17). *Traditional Markets Not Ready Yet to Use PeduliLindungi App: Minister - News en.tempo.co*. https://en.tempo.co/read/1507442/traditional-markets-not-ready-yet-to-use-pedulilindungi-app-minister

Riana, F. (2021, October 8). *Pedulilindungi Integrated with 15 Apps; Health Ministry: Data Encrypted - News en.tempo.co*. TEMPO.CO. https://en.tempo.co/read/1515052/pedulilindungi-integrated-with-15-apps-health-ministry-data-encrypted

Ross, G. M. (2021). I use a COVID-19 contact-tracing app. Do you? Regulatory focus and the intention to engage with contact-tracing technology. *International Journal of Information Management Data Insights*, 1(2), 100045.https://doi.org/10.1016/j.jjimei.2021.100045

Rosseel, Y. (2012). lavaan : An R Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2). https://doi.org/10.18637/jss.v048.i02

Sakib, N., Bhuiyan, A. K. M. I., Hossain, S., Al Mamun, F., Hosen, I., Abdullah, A. H., Sarker, M. A., Mohiuddin, M. S., Rayhan, I., Hossain, M., Sikder, M. T., Gozal, D., Muhit, M., Islam, S. M. S., Griffiths, M. D., Pakpour, A. H., & Mamun, M. A. (2022). Psychometric Validation of the Bangla Fear of COVID-19 Scale: Confirmatory Factor Analysis and Rasch Analysis. *International Journal of Mental Health and Addiction, 20*(5), 2623–2634. https://doi.org/10.1007/s11469-020-00289-x

Seto, E., Challa, P., & Ware, P. (2021). Adoption of COVID-19 Contact Tracing Apps:A Balance Between Privacy and Effectiveness. *Journal of Medical Internet Research*, *23*(3), e25726.

Soper, D.S. (2023). A-priori Sample Size Calculator for Structural Equation Models [Software]. Available from https://www.danielsoper.com/statcalc

Sun, R., Wang, W., Xue, M., Tyson, G., Camtepe, S., & Ranasinghe, D. C. (2021, May). An empirical assessment of global COVID-19 contact tracing applications. In *2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE)* (pp. 1085-1097). IEEE.

Suryaatmadja, S., & Maulani, N. (2020). Contributions of space technology to global health in the context of covid-19. *Jurnal Administrasi Kesehatan Indonesia, 8*(1), 60–73.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tomczyk, S., Barth, S., Schmidt, S., & Muehlan, H. (2021). Utilizing Health Behavior Change and Technology Acceptance Models to Predict the Adoption of COVID-19 Contact Tracing Apps: Cross-sectional Survey Study. *Journal of Medical Internet Research*, *23*(5), e25447. https://doi.org/10.2196/25447

Trang, S., Trenz, M., Weiger, W. H., Tarafdar, M., & Cheung, C. M. K. (2020). One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps. *European Journal of Information Systems*, *29*(4), 415–428. https://doi.org/10.1080/0960085X.2020.1784046

Tretiakov, A., & Hunter, I. (2021). User Experiences of the NZ COVID Tracer App in New Zealand: Thematic Analysis of Interviews. *JMIR MHealth and UHealth*, *9*(9), e26318. https://doi.org/10.2196/26318

Ukpabi, D., Olaleye, S., Karjaluoto, H. (2021). Factors Influencing Tourists' Intention to Use COVID-19 Contact Tracing App. In: Wörndl, W., Koo, C., Stienmetz, J.L. (eds) *Information and Communication Technologies in Tourism 2021*. Springer, Cham. https://doi.org/10.1007/978-3-030-65785-7_48

Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *14*(4), 337–339. https://doi.org/10.1016/j.dsx.2020.04.012

Velicia-Martin, F., Cabrera-Sanchez, J.-P., Gil-Cordero, E., & Palos-Sanchez, P. R. (2021). Researching COVID-19 tracing app acceptance: incorporating theory from the technological acceptance model. *PeerJ Computer Science*, *7*, e316. https://doi.org/10.7717/peerj-cs.316

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Verma, J., & Mishra, A. S. (2020). COVID-19 infection: Disease detection and mobile technology. *PeerJ*, *8*, e10345. https://doi.org/10.7717/peerj.10345

Vogels, E. A. (2019, September 9). *Millennials stand out for their technology use | Pew Research Center*. Pew Research Center. https://www.pewresearch.org/fact-tank/2019/09/09/us-generations-technology-use/

von Wyl, V., Höglinger, M., Sieber, C., Kaufmann, M., Moser, A., Serra-Burriel, M., Ballouz, T., Menges, D., Frei, A., & Puhan, M. A. (2021). Drivers of Acceptance of COVID-19 Proximity Tracing Apps in Switzerland: Panel Survey Analysis. *JMIR Public Health and Surveillance*, *7*(1), e25701. https://doi.org/10.2196/25701

Walrave, M., Waeterloos, C., & Ponnet, K. (2020). Adoption of a contact tracing app for containing COVID-19: A health belief model approach. *JMIR Public Health and Surveillance*, *6*(3), e20572. https://doi.org/10.2196/20572

Walrave, M., Waeterloos, C., & Ponnet, K. (2021). Ready or Not for Contact Tracing? Investigating the Adoption Intention of COVID-19 Contact-Tracing Technology Using an Extended Unified Theory of Acceptance and Use of Technology Model. *Cyberpsychology, Behavior, and Social Networking*, *24*(6), 377–383. https://doi.org/10.1089/cyber.2020.0483

Watkins, M. W. (2018). Exploratory Factor Analysis: A Guide to Best Practice. *Journal of Black Psychology*, *44*(3), 219–246. https://doi.org/10.1177/0095798418771807

Whitelaw, S., Mamas, M. A., Topol, E., & Van Spall, H. G. C. (2020). Applications of digital technology in COVID-19 pandemic planning and response. *The Lancet Digital Health*, *2*(8), e435–e440. https://doi.org/10.1016/S2589-7500(20)30142-4

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and psychological measurement, 73*(6), 913-934. https://doi.org/10.1177/0013164413495237

Ye, J. (2020). The Role of Health Technology and Informatics in a Global Public Health Emergency: Practices and Implications From the COVID-19 Pandemic. *JMIR Medical Informatics*, *8*(7), e19866. https://doi.org/10.2196/19866

Zimmermann, B. M., Fiske, A., Prainsack, B., Hangel, N., McLennan, S., & Buyx, A. (2021). Early perceptions of COVID-19 contact tracing apps in German-speaking countries: Comparative mixed methods study. *Journal of Medical Internet Research, 23*(2), e25525. https://doi.org/10.2196/25525

Authors' Note

Acknowledgement is owed to the author's family, notably for their assistance in disseminating the questionnaire, alongside the contributions made by Iskandar's peers and the extended family of Uung Adzkur towards bolstering this research effort..

All correspondence should be addressed to:
Ikhsan Fuady
Universitas Padjadjaran
Sumedang, Indonesia
ikhsan.fuady@unpad.ac.id

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu

Appendix

Measurements of Constructs

Construct and Item	Measurement	Scale	Reference
Perceived Usefulness (PU)		5-point Likert Scale	Tomczyk et al. (2021)
pu1	PeduliLindungi can improve the tracing of infection chains.		
pu2	PeduliLindungi is a good opportunity to reduce my personal infection risk.		
pu3	PeduliLindungi helps the implementation of quarantine.		
pu4	PeduliLindungi can reduce the infection risk of other people.		
pu5	PeduliLindungi is effective in informing the public about potential infections.		
pu6	PeduliLindungi is effective in protecting me against potential infections		
Perceived Ease of Use (PEase)		5-point Likert Scale	Tomcyzk et al. (2021)
pease1	Feature of Pedulilindungi is clear and easy to operate.		
pease2	It would be easy for me to become competent in using the app.		
pease3	Using the app would be easy for me.		
pease4	Learning to use the app would be easy for me.		
Attitude Towards (ATT)	*(rate Pedulilindungi from)*	5-point semantic differential	Tomcyzk et al. (2021)
att1	Highly useless to highly useful		
att2	Highly unsafe to highly safe		
att3	Awful to excellent		
att4	Highly unobliging to highly helpful		
Intention to Use (Intent)		5-point Likert Scale	Velicia-Martin et al. (2021)
intent1	I intend to use this App in the future.		
intent2	I will try to use this App in my daily life		
intent3	I intend to use this App frequently		
Trust (TRU)		5-point Likert Scale	Oldeweme et al. (2021)
tru1	Pedulilindungi is trustworthy.		
tru2	I trust Pedulilindungi keeps my best interests in mind.		
tru3	Pedulilindungi will keep promises it makes to me.		
tru4	I believe in the information that Pedulilindungi provides me.		

Trust in Government (GOV)		5-point Likert Scale	Oldeweme et al. (2021)
gov1	I think I can trust state government agencies.		
gov2	State government agencies can be trusted to carry out online offerings faithfully.		
gov3	I trust state government agencies keep my best interests in mind.		
gov4	In my opinion, state government agencies are trustworthy.		
Privacy Concern (PRIVAT)		5-point Likert Scale	Oldeweme et al. (2021)
privat1	Pedulilindungi would collect too much information about a user.		
privat2	I would be concerned about my privacy when using Pedulilindungi.		
privat3	I have doubts as to how well my privacy is protected while using Pedulilindungi.		
privat4	My personal information would be misused when Pedulilindungi is running.		
privat5	My personal information would be accessed by unknown parties when using Pedulilindungi in my everyday life.		
Social Influence (SOCIAL)		5-point Likert Scale	Tomcyzk et al. (2021)
social1	Most people who are important to me (e.g. family) think that I should use such an app.		
social2	Many people close to me think that I should use such an app.		
social3	Other people expect me to use such an app.		
social4	My family expects me to use such an app.		