User Acceptance Analysis on Tele counseling App

Azizah Ainun Fitriani
Master of Management Study Program
Faculty of Economy and Business
Telkom University
Bandung, Indonesia
azizahf@student.telkomuniversity.ac.id

Maya Ariyanti
Lecturer at Master of Management
Faculty of Economy and Business
Telkom University
Bandung, Indonesia
ariyanti@telkomuniversity.ac.id

Heppy Millanyani
Lecturer at Master of Management
Faculty of Economy and Business
Telkom University
Bandung, Indonesia
heppymill@telkomuniversity.ac.id

Abstract

This research aims to study users' acceptance in tele counseling via mobile app during global pandemic COVID-19. The research model adopts Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model with modifications including adding Perceived Risk variable and omitting Experience moderating variable. Structural Equation Modelling (SEM) was used to predict the relationship between dependent and independent variables. Partial Least Square (PLS) was used in statistical analysis. The result found that Effort Expectancy, Facilitating Condition, Social Influence and Hedonic Motivation doesn't have significant effect on Reuse Intention. This model explains 63.5% (R^2 = 0.635) of variability of Reuse Intention and 55.3% (R^2 = 0.553) of variability of Reuse Behavior. This research also analyses how gender and age moderates the independent and dependent variables. It is found that age only moderates Price Value towards Reuse Intention and Reuse Intention towards Reuse Behavior while gender doesn't have moderating effect at all. This study provides new insight on factors affecting users' acceptance especially in the context of mobile tele counseling app.

Keywords
Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), tele counseling, mobile app, reuse intention, reuse behavior.

1. Introduction
The outburst of COVID-19 two years ago put the world in a sudden state of change. Many activities were disturbed and even put into halt. Lockdowns lasted for weeks, even months in some countries. This put people in shock and cause the rise of mental health disruption. The pandemic disrupted mental health service in 93% countries around the

world (WHO 2020). Meanwhile, the demand for mental health services keeps rising. In a survey by WHO (2020), as many as 67% of countries encounter disruption in counseling and psychotherapy.

But not for long, people started to adapt and adjust their life such as logistics, business, and especially healthcare. This include migrating their daily activity into virtual. Online health consultation has been around for a while, but as the need arises, more providers started to shift into the virtual world. Even so, 70% of countries that have adopted teletherapy still found gap in this technology adoption (WHO 2020).

In Indonesia, a survey by Association of Indonesian Psychiatrists shows 69% of their respondents experience psychological problems. A total of 68% of them experience anxiety, 67% experience depression, and 77% experience psychological trauma. The respondents were primarily consisted of women (72%) (PDSKJI 2020). The ideal psychiatrist to patient ratio recommended by WHO is 1:30000 (Kemendagri 2021). With Indonesia's total population, Indonesia needs at least nine million psychiatrists. On the other side, there are 45 psychiatric hospitals in 34 provinces in Indonesia (Sari 2020). Tele mental health or telepsychology can mitigate this problem by providing more mental health workers through accessible platform.

One of the mental health platforms in Indonesia is Riliv. The mobile app provides several of services to support one's mental health needs. They provide online counseling and features such as mood tracker, journaling, meditation, and breathing exercise. In 2020, the app download rose 50% with 300% rise in number of users. The CEO, Maximillian, said this was triggered by the pandemic situation (Suminar 2020). On the other hand, a preliminary survey conducted shows that 3 of 10 Riliv users considered in switching to other mental health provider app. This raise questions such as what the reuse behavior in Riliv users like is and what factors affecting their reuse intention and behavior.

Previous studies have showed factors affecting health app adoption. Research by Salgado et al. (2020) analyzed factors affecting mobile health app among patient with chronic and non-chronic illness. Alam et al. (2020) analyzed factors influencing mobile health services in developing country using UTAUT2 model. Research by Tavares and Oliveira (2016) studied health portal service adoption using UTAUT2 framework and adding Chronic Disease as a moderating variable. Hoque and Sorwar (2017) studied factors of mobile health service adoption, focusing on elders. This research used UTAUT model with modification by adding Technology Anxiety and Resistance in Change. Napitupulu et al. (2021) studied factors influencing telehealth acceptance during the pandemic in Indonesia. This research modified UTAUT framework by adding Doctor's Opinion and Computer Anxiety.

Several research studied the contribution of Perceived Risk in technology adoption. Such as research done by Chao (2019) which studied factors in behavioral intention to use mobile learning service with Perceived Risk as a moderating variable. Indrawati and Tohir (2016) studied the acceptance of Smart Metering using a modified UTAUT2 framework which includes Perceived Security and Risk. Research by Egea and Gonzalez (2011) studied the acceptance of healthcare systems from physicians' perspective using TAM with trust and risk factors. According to authors' knowledge and literature review, there is not many studies on acceptance of mental health mobile app yet. This study contributes to the application of UTAUT2 in context of mental health mobile app acceptance.

1.1 Objectives

This research aims to study users' acceptance in tele counseling via mobile app in midst of global pandemic COVID-19. By using a modified UTAUT2 model, this study analyzes factors influencing the technology acceptance which includes Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), Habit (H), and Perceived Risk (PR) and their effects on Reuse Intention (RI) and Reuse Behavior (RB). This study also analyzes age and gender as moderating effects between the factors and Reuse Intention.

2. Literature Review

In the context of technology adoption, TAM has been commonly used as a model that can predict user acceptance of a technological innovation. However, according to Holden and Karsh (2010) in Alam et al. (2020), TAM was not developed specifically for the health care context. The UTAUT2 model developed by Venkatesh et al (2012) aims to measure consumer behavior in individual context up to 74% of variability in behavioral intention and 52% of variability in technology use, which is better than the previous one. This model has been applied into studies in health app acceptance. Research done by Alam et al. (2020) modified UTAUT model by adding Price Value due to research being held in a developing country where people are more price sensitive. This model explains 62% of variability in behavioral intention and 28% in use behavior. Study Salgado et al. (2020) found that UTAUT2 explains 66% of variability in behavioral intention and 54% in use behavior.

Meanwhile, there are other factors that might influence technology acceptance. According to Saptandari (2018), tele counseling has risk on user data leakage. The influence of this perceived risk, as stated in Chao (2019), is that the higher the risk that a person perceives, the less likely they are to use the technology. In their study, Chao (2019) applied Perceived Risk as a moderating variable between Effort Expectancy and Behavioral Intention, and Performance Expectancy and Behavioral Intention. The result shows Perceived Risk doesn't moderate Effort Expectancy and Behavioral Intention and affects negatively towards Behavioral Intention.

This research adopts UTAUT2 model by Venkatesh et al. (2012) with modifications. Perceived Risk is added as an independent variable. This addition aims to examine its relationship with Reuse Intention. Also, moderating variable Experience is excluded as this research is cross-sectional research. Thus, the proposed research model is depicted in Figure 1.

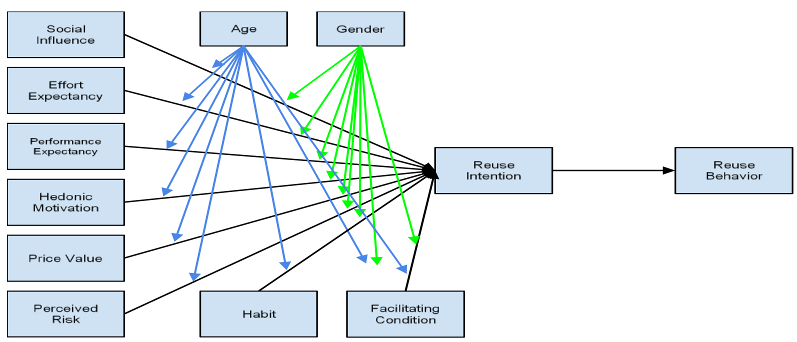

Figure 1. Research model

The hypotheses proposed in this research are summarized in the following Table 1.

Table 1. Hypotheses

Performance Expectancy	
1.	Performance Expectancy has a positive and significant effect towards Reuse Intention
1a.	Age moderates the effect of Performance Expectancy towards Reuse Intention significantly
1b.	Gender moderates the effect of Performance Expectancy towards Reuse Intention significantly
Effort Expectancy	
2.	Effort Expectancy has a positive and significant effect towards Reuse Intention
2a.	Age moderates the effect of Effort Expectancy towards Reuse Intention significantly
2b.	Gender moderates the effect of Effort Expectancy towards Reuse Intention significantly
Social Influence	
3.	Social Influence has a positive and significant effect towards Reuse Intention
3a	Age moderates the effect of Social Influence towards Reuse Intention significantly
3b.	Gender moderates the effect of Social Influence towards Reuse Intention significantly
Facilitating Condition	
4.	Facilitating Condition has a positive and significant effect towards Reuse Intention
4a.	Age moderates the effect of Facilitating Condition towards Reuse Intention significantly
4b.	Gender moderates the effect of Facilitating Condition towards Reuse Intention significantly
Hedonic Motivation	
5.	Hedonic Motivation has a positive and significant effect towards Reuse Intention
5a.	Age moderates the effect of Hedonic Motivation towards Reuse Intention significantly
5b.	Gender moderates the effect of Hedonic Motivation towards Reuse Intention significantly

Price Value	
6.	Price Value has a positive and significant effect towards Reuse Intention
6a.	Age moderates the effect of Price Value towards Reuse Intention significantly
6b.	Gender moderates the effect of Price Value towards Reuse Intention significantly
Habit	
7.	Habit has a positive and significant effect towards Reuse Intention
7a.	Age moderates the effect of Habit towards Reuse Intention significantly
7b.	Gender moderates the effect of Habit towards Reuse Intention significantly
Perceived Risk	
8.	Perceived Risk has a negative and significant effect towards Reuse Intention
8a.	Age moderates the effect of Perceived Risk towards Reuse Intention significantly
8b.	Gender moderates the effect of Perceived Risk towards Reuse Intention significantly
Reuse Intention	
9.	Reuse Intention has a positive and significant effect towards Reuse Behavior

3. Methods

This research is a quantitative study which measure behavior, knowledge, opinion, or attitude accurately (Indrawati 2015). Quantitative method is used to test model or hypotheses (Indrawati, 2015). With this research, authors aim to study the relationship between variables and describe a population or situation (Sekaran and Bougie 2003). Data from sample is collected through online survey.

3.1 Measures

The measurement items in this study contains 38 statements that are adopted from previous studies using UTAUT model. A five-point Likert scale is used to measure each item. Respondents are asked to answer how strong they agree with each statement ranging from "strongly disagree" to "strongly agree". (Table 2)

Table 2. Measurement items

Variable	Reference	Measurement Item	No. Item
Performance Expectancy	Alam, et al., 2020	I find Riliv useful in my life.	PE1
		Riliv increases my chances of getting mental health service.	PE2
		Riliv helps me manage my mental healthcare more quickly	PE3
		Riliv increases my capability to manage my health.	PE4
Effort Expectancy	Semiz and Semiz, 2021	I find Riliv easy to use.	EE1
		The use of Riliv is clear.	EE2
		The use of Riliv is easy to understand.	EE3
		Learning how to use Riliv is easy for me.	EE4
		It is easy for me to become skillful at using Riliv.	EE5
Social Influence	Salgado, et al., 2020	People who are important to me think that I should use Riliv.	SI1
		People who influence my behavior think that I should use Riliv.	SI2
		People whose opinions that I value prefer that I use Riliv.	SI3
Facilitating Condition	Hoque and Sorwar, 2017	I have the resources necessary to use Riliv.	FC1
		I have the knowledge necessary to use Riliv.	FC2
		Riliv is compatible with other technologies I use.	FC3
Hedonic Motivation	Venkatesh, et al., 2012	Using Riliv is fun.	HM1
		Using Riliv is enjoyable	HM2
		Using Riliv is entertaining.	HM3
Price Value	Salgado, et al., 2020	Riliv counseling service is reasonably priced.	PV1
		Riliv services are a good value for the money.	PV2
		At the current price, Riliv provide a good value.	PV3
Habit		I must use Riliv.	H1

	Semiz and Semiz, 2021	The use of Riliv have become a habit for me.	H2
		I am addicted to using Riliv.	H3
		Using mHealth applications have become natural.	H4
Perceived Risk	Chao, 2019	I think using Riliv puts my privacy at risk.	PR1
		Using Riliv exposes me to an overall risk.	PR2
	Im et al., 2008	It is probable that Riliv would not be worth its cost.	PR3
		It is probable that Riliv would frustrate me because of its poor performance.	PR4
		It is uncertain whether Riliv would be as effective as I think.	PR5
Reuse Intention	Venkatesh, et al., 2012	I intend to continue using Riliv in the future.	RI1
		I will always try to use Riliv in my daily life.	RI2
		I plan to continue to use Riliv frequently.	RI3
Reuse Behavior	Hoque and Sorwar, 2017	Using Riliv is a pleasant experience.	RB1
		I use Riliv currently.	RB2
		I spend a lot of time on Riliv.	RB3
	Kristianto, 2021	I will continue to use Riliv as the first choice.	RB4
		I will share information & recommend Riliv to others.	RB5

3.2 Analysis Technique
The model in this research has 8 independent variables and 2 dependent variables. Multivariate dependent techniques is used to analyze several variables at the same time. To predict relationship between dependent and independent variables, this research used VB-SEM techniques with Partial Least Square (PLS). As stated by Indrawati (2017), PLS is more commonly used in analyzing UTAUT model. It can also process small number of data, starting from 38, and large number of data, up to 1000.

The data analysis consists of two steps, which uses measurement model and structural model. Measurement model analysis was done by analyzing model's reliability and validity by their Cronbach Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) score. A model is considered to have a good reliability with CA and CR scored at least 0.7. Meanwhile, a good validity is considered with AVE score at least 0.5. The output is shown in Table 3.

Structural model analysis was done by analyzing R square value and structural paths of dependent variables. This analysis is done by bootstrapping method to test hypotheses proposed in this research in SmartPLS. Path coefficient with t-statistics value of at least 1.645 is considered significant with 5% of error. The output is shown in Table 4 and Table 5.

To measure gender and age's moderating effect, this research used group comparison approach where sample are divided into groups based on gender (male and female) and age (young and adult). Each group is run for path coefficient analysis and then compared with Chin's (2000) equation (Indrawati 2017). T-value required to be at least 1,645 to be considered having a moderating effect. The result for each comparison is presented in Table 6.

4. Data Collection
Primary data was obtained from field study and hypotheses testing by broadcasting online questionnaire using Google Form. The research is conducted in Indonesia among people who are Riliv user. Purposive sampling technique was used for this research. Respondents have the criteria of at least 18 years of age, female, or male, use Riliv since pandemic (March 2020). The data was collected from June until July 2022. A total of 288 respondents participated this study. After data processing, 50 of them didn't fulfill the criteria and thus excluded, leaving 238 data of respondents to be analyzed. Most respondents were female (89,4%). Also, most of them were in the age range of 18-24 years old. The summary of respondents is presented in Table 3. Secondary data was obtained from literature review of research on technology adoption, especially on health app services. Official data from government and health organizations were also used to complement data requirement in this research. (Table 3)

Table 3. Respondent profiles

		Frequency	Percentage
Gender	Male	26	10.6%
	Female	212	89.4%
Age	18-24	179	75.2%
	25-31	59	24.7%

5. Results and Discussion

5.1 Measurement Model

Measurement model analysis result as seen on Table 4 shows each variable has the value of CA and CR above 0.7 and the value of AVE above 0.5. This indicates items in model are valid and reliable.

Table 4. Summary of measurement model analysis

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
EE	0.885	0.916	0.685
FC	0.715	0.837	0.632
H	0.918	0.942	0.804
HM	0.917	0.948	0.858
PE	0.846	0.897	0.687
PR	0.867	0.901	0.645
PV	0.869	0.918	0.789
RB	0.806	0.866	0.565
RI	0.843	0.905	0.761
SI	0.924	0.952	0.867

5.2 Structural Model

The structural model is evaluated by examining R square value. The result can be seen in Table 5. Overall, the model explains 63.5% of variability in RI and 55.3% of variability in RB. Indrawati (2017) stated R^2 result with value 0.67 is considered as good, 0.33 as moderate, and 0.19 as weak. According to this, the endogenous variables used in the model have a good explanatory ability This result is statistically higher than previous model by Alam et al. (2020) (Behavioral Intention $R^2 = 0.62$, Usage Behavior $R^2 = 0.28$), Mohadis and Ali (2018) (Behavioral Intention $R^2 = 0.38$), Napitupulu et al. (2021) (Behavior Intention to Use = 0.442), and Tavares et al. (2016) (Behavioral Intention $R^2 = 49.7$, Usage Behavior $R^2 = 26.8$).

Bootstrapping result shows path coefficient, which shows how much a dependent variable affects independent variable, and t-statistics value to test our hypotheses. The summary of structural model can be seen in Table 6. T-statistics value show that relationship between PE and RI ($t = 4.447$), PV and RI ($t = 2.365$), PR and RI ($t = 2.695$), H and RI ($t = 12.762$), and RI and RB ($t = 21.148$) are significant. This indicates hypotheses 1, 6, 7, 8, and 9 are supported.

Table 5. Summary of R square analysis

	R Square
RB	0.553
RI	0.635

PE significantly affects RI. This aligns with studies by Semiz and Semiz (2021), Napitupulu et al. (2021), Alam et al (2020), Salgado et al (2020), and Hoque and Sorwar (2017) on mobile health app. Respondents in this study consider the app's performance in solving their mental health problem affects their intention to reuse the app.

PV was found to have significant effect towards RI. Although the significant effect of PV has been examined in studies on technology adoption before, not many covers health app. Most health app studied before does not cost money to access its features. Although, a study by Alam et al. (2020) on mobile health adoption in a developing country found that PV does not have a significant effect towards behavioral intention. Riliv itself uses a subscription model for their content and pre-paid counseling. The significance in relationship between PV and RI indicates that price plays an important role in app adoption by users. Respondents may be price sensitive as the characteristic of people in developing country, as presumed by Alam et al. (2020) previously. The emerging of mental health apps may also be influenced in perceiving prices as different providers offer the same service with different prices.

Table 6. Summary of structural model analysis

	Original Sample (O)	T Statistics (|O/STDEV|)	T Table	Conclusion
EE -> RI	0.041	0.901	1.645	Not supported
FC -> RI	-0.015	0.352	1.645	Not supported
H -> RI	0.580	12.762	1.645	Supported
HM -> RI	-0.013	0.246	1.645	Not supported
PE -> RI	0.221	4.447	1.645	Supported
PR -> RI	-0.127	2.695	1.645	Supported
PV -> RI	0.117	2.365	1.645	Supported
RI -> RB	0.743	21.148	1.645	Supported
SI -> RI	0.014	0.269	1.645	Not supported

PR has a significant effect on RI. Like PV, PR has been previously examined in studies on technology adoption, but not many in health app. In previous study by Chao (2019), PR was examined as a moderating variable. The result show PR has a negative moderating effect on EE in mobile learning. While in this study, PR is an independent variable affecting RI and has a negative relationship with RI. This aligns with Zhao et al. (2018) where they stated, the higher the risk that a person perceives, the less likely they are to use the technology. The negative relationship indicates that the low risk perceived by users influence them to reuse the app. (Table 6)

H was found to have a significant effect on RI. This aligns with studies by Salgado et al. (2020) and Semiz and Semiz (2021) on mobile health application. Among variables affecting RI, H has the highest t-statistic and path coefficient value. This indicates H is the strongest predictor of RI. The habit respondents established while using the app influence them to reuse the app.

RI was also found to have a significant effect on RB. This is contrary to previous study on mobile health app by Salgado et al. (2020). The study found that behavioral intention does not influence use behavior, meaning behavior intention does not translate in actual usage of the app. Even so, this study aligns with traditional conclusion where users' intention to use influence the actual app usage. Therefore, respondents are more likely to reuse Riliv app.

Meanwhile, relationship between EE and RI, FC and RI, HM and RI, and SI and RI have values below 1,645 (0.901, 0.352, 0.246, and 0.269 respectively). Thereby, hypotheses 2, 3, 4, and 5 are not supported. Although they are against traditional conclusion, several previous studies also found the insignificance of effect on these variables. Study by Mohadis and Ali (2018) found that EE does not have significant effect on behavioral intention among office workers. Mohadis and Ali (2018) stated that their participants are well-experienced smartphone users so their interaction with new technology would be easy and intuitive. In context of this study, it might also be the case. Participants in this study are aged 18-31 which makes them born after 1990. They can be categorized as digital natives as they grew up with technology and experience the fast-changing trends. This may affect how they perceive the ease of use in new technology. Study by Salgado et al. (2020) also found that EE does not significantly affect behavioral intention in mobile health acceptance.

FC was found to be insignificant on RI. Like EE, respondents do not consider resources as an issue. This might be related to the increasing access in smartphone and internet. Survey by We Are Social (2021) shows 73.7% of total Indonesian population are connected to internet, and 98.2% of Indonesian aged 16-64 have smartphone (Kemp 2021). Study by Salgado et al. (2020) does not find FC to have significant effect on behavioral intention. Salgado et al. (2020) also suggest that the increasing access to mobile phone and internet affect samples' evaluation towards FC.

HM also has no significant effect on RI. Although contrary to traditional theory, this finding aligns with study by Tavares et al. (2016) found that HM has no significant impact on behavioral intention. Tavares et al. (2016) presume the health portal does not promote enjoyment as samples might associate it with disease or health problem. HM is defined as enjoyment or satisfaction of the use of technology. Respondents in this study might not perceive using Riliv as 'fun' or 'entertaining' as this app is used to help users who are feeling not well mentally.

SI was also found to be insignificant on RI. The UTAUT model suggests that social influence plays a significant role in individual's intention to use technology. However, this study does not support it. But this aligns with previous study by Yuan et al. (2015) on health and fitness app. The study presume that the use of the app might depend on what an individual perceives, and not influenced by their peer. Riliv itself is a mental health app. Mental health treatment or services can be very personal and not a one-size-fits-all. What works for one might not for others. Therefore, respondents might not consider others' opinion to use the app.

5.3 Moderating Effect

Group comparison approach was used to examine age and gender's moderating effect. Previous variables with no significant effect (EE, FC, HM, and SI) are excluded in this analysis. After dividing data into groups based on age and gender, each of the group data is examined by their path coefficient and compared. Result can be seen on Table 7.

Table 7. t-value of moderator variables

	Age		Gender	
	t-value	Conclusion	t-value	Conclusion
H -> RI	0.99	not supported	0.32	not supported
PE -> RI	-1.39	not supported	-0.86	not supported
PR -> RI	1.57	not supported	-0.58	not supported
PV -> RI	2.07	supported	1.80	not supported

T-value for each variable with age as moderating effect shows no significant difference except for relationship between PV and RI. This indicates only hypotheses 7a are supported, meaning age has a significant role in PV affecting RI. Meanwhile, t-value for each variable with gender as moderating effect shows no significant difference at all. Therefore, hypotheses 1a, 6a, 7a, and 8a are not supported. This study found that gender does not have a significant role in PE, PR, PV, and H affecting RI.

5.4 Proposed Improvements

The model used in this research was adapted from previous UTAUT2 model by Venkatesh et al. (2012). Results from this study were able to explain factors influencing the technology acceptance which includes performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, habit, and perceived risk and their effects on reuse intention and reuse behavior. This study also analyzes age and gender as moderating effects between the factors and users' intention to reuse. However, this study has several limitations.

Samples from this study are aged ranging from 18-31. This is due to questionnaire distribution among people of mentioned age range. However, current author does not have the overall app user data which does not rule out the possibility of users above mentioned age range. Thus, further study is advised to have larger age range that includes all age of app user.

Samples from this study are also more saturated on women rather than men. Although this aligns with survey by PDSKJI (2020) mentioned before where respondents are primarily women, this still leave a room for improvement. Future study may use stratified sampling based on overall app used data. This way, samples can be more proportionally distributed.

6. Conclusion

In studying a mental health app, a modified UTAUT model was used to examine factors affecting users' intention and behavior in reusing the app. Result shows that performance expectancy, price value, and habit significantly influence users' reuse intention. The additional variable perceived risk also found to be significantly influencing reuse intention. The result indicates habit as the strongest predictor of reuse intention. Gender was found to not have significant effect in moderating independent variables with reuse intention. Age was found to have significant effect only in moderating price value with reuse intention. The overall model has a good explanatory ability, and is statistically better than models from preceding studies on health app.

Result from this study show variables that are significant to users' intention and behavior in reusing the app. In order to increase the usage rate of the application, it is recommended that service providers focus on their app performance and service pricing to compete with other providers. They should also keep in mind to not put their users' data and privacy at risk. Age was found to have a significant role in moderating PV towards RI. However, this study has yet to conclude the reason from each age group. Further research should study factors influencing users' evaluation on price value on different age groups. This can help mental health app providers set their pricing strategy for different segment of users.

References

Chao, C. M., Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model, *Front. Psychol.* 10(1652), 2019. doi: 10.3389/fpsyg.2019.01652

COVID-19 disrupting mental health services in most countries, WHO survey, World Health Organisation, 2020. Available: https://www.who.int/news/item/05-10-2020-covid-19-disrupting-mental-health-services-in-most-countries-who-survey Accessed on October 15, 2021

Distribusi Penduduk Indonesia Per Juni 2021: Jabar Terbanyak, Kaltara Paling Sedikit, Available: https://dukcapil.kemendagri.go.id/berita/baca/809/distribusi-penduduk-indonesia-per-juni-2021-jabar-terbanyak-kaltara-paling-sedikit Accessed on November 18, 2021.

Hoque, M., and Sorwar, G., Understanding Factors Influencing the Adoption of mHealth by the Elderly: An Extension of the UTAUT Model, *International Journal of Medical Informatics.* 2017.

Im, I., Kim, Y., and Han, H. J., The effects of perceived risk and Technology typing users acceptance of Technologies, *Information & Management*, vol. 45, pp. 1-9. 2008

Indrawati and Tohir, L.M., Predicting smart metering acceptance by residential consumers: An Indonesian perspective, *Fourth International Conference on Information and Communication Technologies (ICoICT),* 1-6. 2016.

Indrawati and Yuliansyah, S., Adoption Factors of Online-Web Railway Ticket Reservation Service (A Case From Indonesia), *5th International Conference on Information and Communication Technology (ICoIC7),* 1-6. 2017.

Kemp, S., Digital 2021: Indonesia. Available: https://datareportal.com/reports/digital-2021-indonesia Accessed on November 17, 2021.

Kristianto, Y. E., Strategy of Technology Acceptance Model Utilization for Halodoc, a Telehealth Mobile Application with Task Technology Fit as Moderator Variable, *International Journal of Innovative Science and Research Technology*, vol. 6, no. 8. 2021.

Mental Health: Strengthening Our Response, World Health Organization, 2018. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response Accessed on October 15, 2021

mHealth: New Horizons For Health Through Mobile Technologies: Second Global Survey On eHealth, World Health Organization, 2011. Available: https://apps.who.int/iris/handle/10665/44607 Accessed on October 15, 2021

Napitupulu, D., Yacub, R., and Putra, A. H. P. K., Factor Influencing of Telehealth Acceptance During COVID-19 Outbreak: Extending UTAUT Model, *International Journal of Intelligent Engineering and Systems,* vol. 14, no. 3, 2021

Masalah Psikologis Di Era Pandemi Covid-19, 2020, Available: http://www.pdskji.org/home Accessed on October 10, 2021

Sari, O. K., Ramdhani, N., and Subandi., Kesehatan Mental di Era Digital: Peluang Pengembangan Layanan Profesional Psikolog. *Media Penelitian dan Pengembangan Kesehatan*, vol. 30, no. 4, pp. 337-348, 2020.

Sekaran, U., and Bougie, R., *Research Methods For Business: A Skill-Building Approach.* John Wiley & Sons. England. 2016.

Semiz, B.B., and Semiz, T., Examining Consumer Use Of Mobile Health Applications By The Extended Utaut Model. *Bmij,* vol. 9, no. 1, pp. 267-281. 2021.

Suminar, A., Tiga Startup Indonesia Tumbuh di Tengah Pandemi. Suara Surabaya. Available: https://www.suarasurabaya.net/ekonomibisnis/2020/tiga-startup-indonesia-tumbuh-di-tengah-pandemi/ Accessed on November 12, 2021

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D., User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly,* vol. 27, no. (3), pp. 425-478. 2003.

Venkatesh, V., Thong, J. Y. L., and Xu, X., Consumer Acceptance and Use of Information Technology: Extending the Unified Theory. *MIS Quarterly,* vol. 36, no. (1), pp. 157-178. 2012.

Zhao, Y., Ni, Q., and Zhou, R., What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age, *International Journal of Information Management*, vol. 43, pp. 342-350. 2018.

6 Ways To Take Care Of Your Mental Health And Well-Being This World Mental Health Day, WHO News Release, 2021. Available: https://www.who.int/westernpacific/about/how-we-work/pacific-support/news/detail/07-10-2021-6-ways-to-take-care-of-your-mental-health-and-well-being-this-world-mental-health-day Accessed on October 15, 2021

Biography

Azizah Ainun Fitriani is a postgraduate student, currently studying Management at School of Economy and Business, Telkom University. She earned her bachelor's degree in communication science from Telkom University in 2020. Her area of interest includes digital marketing and management.

Maya Ariyanti is a lecturer for Master of Management program at School of Economy and Business, Telkom University. She graduated from the Management Undergraduate program of Parahyangan University, Bandung (1991-1996), the Management Graduate of Padjadjaran University (1997-1999), and Postgraduate Business Management of Padjadjaran University (2004-2009). Her attention was focused on Marketing, Management Information Systems, Telecommunication Business, Business Management, and Business Strategy.

Heppy Millanyani is a lecturer for Master of Management program at School of Economy and Business, Telkom University. She expertise in consumer behavior, social media marketing, marketing analysis.