Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://www.jds.or.kr/
http://dx.doi.org/10.15722/jds.21.07.202307.117

Generation YZ's E-Healthcare Use Factors Distribution in COVID-19's Third Year: A UTAUT Modeling

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Received: March 19, 2023. Revised: April 30, 2023. Accepted: July 05, 2023.

Abstract

Purpose: With the number of COVID-19 cases declining and generational differences among how people use mobile apps, including health service apps, the goal of this research is to identify and analyze the factors that affect people's attitudes when using the Halodoc health service app during the third year of the pandemic. **Research design, data, and methodology:** This study proposes a quantitative analysis method based on PLS-SEM modeling. This study has used a questionnaire survey to collect randomized data from 268 Halodoc users from generations Y and Z in Jakarta. **Results:** Both the Y and Z generations believe there is a significant usefulness factor in the attitude toward using the application. The start of the pandemic period demonstrates that the urgency of using health service applications is no longer determined by performance expectations, effort, or social panic, but rather by these applications' usability. **Conclusions:** Even though a health service application is no longer considered an urgent service or a priority need, attitudes, and behaviors in using it emphasize the aspect of long-term benefits. These findings supplement other considerations and understandings in application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model in explaining attitudes and intention behaviors.

Keywords : Attitude, Usage Behavior, Health Service Applications, UTAUT Model, Factors Distribution

JEL Classification Code: D39, M10, O33, L84, L86

1. Introduction

Even though the trend of cases has been sloping downward in Indonesia during the third year of the COVID-19 pandemic, awareness of the need to protect oneself continues. The distribution of mobile health services, or e-health, has also grown more accessible to the public. An e-health service provider company strives to provide the best

* The authors would like to thank Bunda Mulia University for supporting this study.

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service possible so that the public will accept it. As a result, various factors influencing user behavior emerge when these services are used or adopted. Apart from the sustainability of existing technology adoption models, conceptual discussion of digitalization in health services is ongoing in several studies using various concepts and approaches, such as the Technology Acceptance Model (TAM) (Dash et al., 2019; Kataria et al., 2021; Klingberg et al., 2019) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Garavand et al., 2019; Rouidi et al., 2022). However, such models do not escape the addition or adjustment of variables that are implemented in various places and conditions.

According to (Jadil et al., 2021), such variables influence an individual's intention to use an app. According to specific research findings, variables such as trust-risk (Arfi, Nasr, Khvatova, et al., 2021), self-efficacy, effort expectations, performance expectations, facilitation conditions (Shiferaw et al., 2021; Yu et al., 2021), facilitating conditions (Gu et al., 2021), and social influence impact usage behavior within health applications (Napitupulu et al., 2021).

The differences among the research results above indicate that a user's behavior regarding e-health services will be heavily influenced by the reliability of e-health service distribution and the user's characteristics, one of which is the user's age. Age groups, which can be classified into generations, have different characteristic tendencies regarding the adoption or use of an online service, whether application-based or website-based. This is especially true in younger age groups, such as generation Y (born 1980–1994) and generation Z (born after 1995) (Bassiouni & Hackley, 2014; Bednall et al., 2012). These two generations tend to be essentially open and literate, and find movement among technology services easy (Christian, Wibowo, et al., 2022).

This study is related to the central place theory concept, with an emphasis on the distribution of services to consumers. This study's goals include revealing which factors will influence attitudes and behavior in using e-health services, particularly regarding generations Y and Z. This theory also applies to the service distribution network, which involves areas such as large cities. This relates to the balance between a company's efforts and a community's intention to use e-health services.

The dissimilarities in the research results discussed above represent the research gap this study aims to address. Furthermore, the sensitive usage behavior of generations Y and Z generations is important for e-health service research. This research proposal focuses on the variables that influence how people use e-health services. Based on these factors, the purpose of this study is to examine the antecedent variables that influence the use of e-health services. The novel aspect of this research involves testing the UTAUT model for healthcare applications during times when the pandemic remains ongoing, despite declining numbers of cases. This research may explain why the benefits of using an application are no longer a pressing requirement.

2. Literature Review

2.1. UTAUT Model

The UTAUT model has been used to predict how people will react to new technology applications in a variety of settings, including the health sector (Garavand et al., 2019; Venkatesh et al., 2003; Venugopal et al., 2019). This model, in general, describes the internal and external factors affecting a technological application. The internal perspective involves several factors, including performance expectancy, effort expectancy, attitude toward using technology, perceived ease of use, perceived usefulness, and facilitating conditions. The external perspective can be explained via the social influence factor. The user's perception of the benefits of the system or application used is described by performance expectancy (Kalavani et al., 2018; Pai & Huang, 2011). In addition, this emphasizes the extent to which users benefit from an application's features. Such benefits are secondary to the effort required to use an app. In other words, effort expectancy is defined as "the perception of how simple a system or application is to use" (Chauhan & Jaiswal, 2016; Kijsanayotin et al., 2009).

Furthermore, attitude toward technology is defined as a reflection or form of intellectual and emotional mindset that demonstrates how individuals think about or comprehend an object (Tilahun & Fritz, 2015; Yehualashet et al., 2015). An application's use is unrelated to the user's perception of its ease and usefulness. Perceived ease of use emphasizes a system's or application's ease of use, whereas perceived usefulness emphasizes improving the outcome or process of using a system or application (Bakken et al., 2006; Martínez et al., 2006). Another factor, facilitating conditions, describes the perception of how effectively infrastructure and organizational conditions support or facilitate the use of systems or applications (Shiferaw et al., 2021). Lastly, social influence describes a user's perception of how much other people or close friends support the use of a new system or application (Rasmi et al., 2020).

2.2. Hypothesis Development

2.2.1. Performance expectancy and behavioral intention

In most studies, individual behavioral interest in technology use is largely determined by performance expectations (Abbad, 2021; Alabdullah et al., 2020;

Mengesha, 2020; van der Vaart et al., 2016). However, in contrast, research results also show that performance expectations may not have an impact on users' intentions to use e-health applications, although in general this explains the opposite result (Arfi, Nasr, Kondrateva, et al., 2021). This distinction explains why performance expectations do not always have direct impacts (Shiferaw et al., 2021). Furthermore, even if there are related supporting variables, performance expectations and usage intentions have a relationship (Raza et al., 2020). Based on the foregoing explanations, this study proposes the following hypotheses (H):

H1a: Performance expectancy significantly affects behavioral intention.
H1b: Performance expectancy, as mediated by behavioral intention, significantly affects usage behavior.

2.2.2. Effort Expectancy and behavioral intention

In general, the effort required to use mobile technology should not pose a deterrent. This is consistent with Garavand et al. (2019), who found a significant relationship between expected effort and intention to use. Rahimi et al. (2018) identified a related element, which is that the use of mobile technology should include a "fun factor." Situational interventions, for example, can have different effects than indirect effects. In contrast, effort expectations have no effect on behavioral intention (Shiferaw et al., 2021). Based on the approaches described, this study proposes the following hypotheses (H):

H2a: Effort expectancy significantly affects behavioral intention.
H2b: Effort expectancy, as mediated by behavioral intention, significantly affects usage behavior.

2.2.3. Attitude toward using technology and behavioral intention

Undeniably, the people around you, whether family or friends, can have a significant impact on your decision to use an app. Several studies have also demonstrated that social environmental factors influence usage behavior (Alabdullah et al., 2020; Dash et al., 2019). However, social factors may not have much of an impact on the decision to use (Sezgin et al., 2016; Shiferaw et al., 2021). In light of this, there remain differences among the research results in revealing the influence of social factors on usage behavior. As a result, this study advances the following research hypotheses:

H3a: Social influence significantly affects behavioral intention.
H3b: Social influence, as mediated by behavioral intention, significantly affects usage behavior.

2.2.4. Social influence and behavioral intention

A user's attitude toward technology as an application can influence their decision to use it. This is consistent with the findings of several studies, which show that these two variables have a significant relationship (Dash et al., 2019; McKee et al., 2021; Shiferaw et al., 2021). In contrast, for some people, views are simply opinions that aren't strong enough to compel them to act. Monthuy-Blanc et al. (2013) demonstrate this further, explaining the insignificance. Based on these approaches, this study proposes the following hypotheses:

H4a: Attitude toward using technology significantly affects behavioral intention.
H4b: Attitude toward using technology, as mediated by behavioral intention, significantly affects usage behavior.

2.2.5. Facilitating conditions and behavioral intention

Views on the sufficiency of infrastructure, as well as technical and organizational capabilities in the use of applications, can indicate a favorable facilitating condition. This favorable condition will undoubtedly increase people's confidence in using an application; several studies have revealed a significant relationship between these two variables (Alabdullah et al., 2020; Sezgin et al., 2016). Even so, there are times when people do not see the benefit of influencing the intention to use (Shiferaw et al., 2021). Based on this, the current study proposes the following hypotheses:

H5a: Facilitating conditions affects behavioral intention significantly.
H5b: Facilitating conditions, as mediated by behavioral intention, significantly affect usage behavior.

2.2.6. Perceived ease of use and behavioral intention

In general, people will want to use an application if it is simple to use, whereas a difficult method of use will pose an individual barrier to usage (Veríssimo, 2018). Achieving perceived ease of use should not be difficult (Yee et al., 2019). One of the characteristics involved in behavioral intention is the application's ease of use (Susanto & Aljoza, 2015). As a result, this study proposes the following hypotheses:

H6a: Perceived ease of use significantly affects behavioral intention.
H6b: Perceived ease of use, as mediated by behavioral intention, significantly affects usage behavior.

2.2.7. Perceived usefulness and behavioral intention

People are more likely to use an app if they believe it will benefit them and meet their needs (Lee, 2018; Morosan & DeFranco, 2016; Vahdat et al., 2020). According to Yee et al., (2019), the usefulness of an application can be determined based on how well it works and how productive it is. A well-designed application's facilitating conditions reflect adequate infrastructure as well as technical and organizational capabilities for usage. This, of course, will have impacts on attitudes and behaviors in use of the application (Alabdullah et al., 2020; Sezgin et al., 2016). The perception of demands on facilitating conditions diminishes. This is also consistent with the idea that there are times when people do not see the benefit of influencing their intention to use (Shiferaw et al., 2021). Hence, this study proposes the following hypotheses:

H7a: Perceived usefulness significantly affects behavioral intention.

H7b: Perceived usefulness, as mediated by behavioral intention, significantly affects usage behavior.

2.2.8. Behavioral intention and usage behavior

A strong desire to use an application can be a motivator to use it. These two variables have a significant relationship in terms of usage intention and usage behavior (Garavand et al., 2019). Hoque & Bao (2015) and Venugopal et al. (2019) explain the relationship between the two variables, and identify a strong significance. Based on these explanations, the following hypothesis is advanced in this study:

H8: Behavioral intention significantly affects usage behavior.

This study employs a conceptual framework, as shown in Figure 1, based on the developments described above.

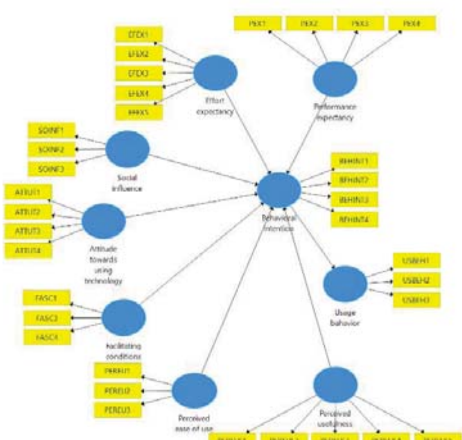

Figure 1: Conceptual framework

3. Research Methods and Materials

3.1. Research Design

This quantitative study employs partial least squares-structural equation modeling (PLS-SEM) and SmartPLS 3.0 as an analysis tool. This model allows for the use of a limited number of samples to simultaneously examine complex structural models. This study makes use of 37 different items. Seven of these are external factors, one is a middleman, and one is internal. Table 1 displays each variable and item. Performance expectancy (four indicators), effort expectancy (five indicators), social influence (three indicators), attitude toward using technology (four indicators), facilitating conditions (five indicators), perceived ease of use (three indicators), and perceived usefulness (five indicators) are examples of exogenous variables. The mediator variable employs four indicators of behavioral intention. Endogenous variables also employ usage behavior, which comprises four indicators.

3.2. Sample and Data Collection

To collect information from the participants in this study, an online survey with randomly assigned questionnaires was used. The survey was conducted between January and February of 2023. Because the exact population size was unknown, the sample size was determined by multiplying the number of indicators by 5 (the minimum sample size) to 10 (the maximum sample size) (Benitez et al., 2020; Willaby et al., 2015). The sample size in this study was determined to be 268 samples in Jakarta meeting the inclusion criteria: generations Y (born 1980–1994) and Z (born 1995 or later) who used the Halodoc health service application during either 2022 or the third year of the COVID-19 pandemic, with 37 items. This app was chosen because it is widely used in Indonesia, particularly during the pandemic. The age criteria for this generation group have then been adjusted based on the Indonesian popular belief that individuals enter the adult age category at 17 years old. These criteria were used as participant profiles at the start of the questionnaire and then adjusted to the filtering criteria described above.

3.3. Analysis Technique

This study employs SmartPLS with structural modeling to analyze the data. The first analysis in this study examines data reliability and validity. The reliability test is based on Cronbach's alpha (CA) and composite reliability (CR) values greater than 0.7, while the validity test is based on outer loading (OL) values greater than 0.7 and average variance extracted (AVE) values greater than 0.5 (Barati et al., 2019; Memon & Rahman, 2014; Wibowo et al., 2023).

Furthermore, this study investigates the model's suitability, as determined by the saturated root mean square (SRMR) < 0.01 and the Nordic fit index (NFI), which needed to be close to 1 to indicate suitability (Hu & Bentler, 1999; Hussain et al., 2018). Meanwhile, the coefficient of determination in this study is determined using adjusted R2 values (< 0.5 = weak; ≥ 0.5 = moderate; ≥ 0.75 = strong). The next analysis is the hypothesis testing analysis, which is based on *p*-values less than 0.05.

Table 1: Variable and item

Variable	Item	
Usage behavior	USBEH1	I intend to use Halodoc's consultation services with doctors in the near future.
	USBEH2	I am willing to do consulting services with doctors at Halodoc if I really need them.
	USBEH3	If I learn that a doctor, I know is on the medical team at Halodoc, I will be even more inclined to use the service's consulting services with doctors.
	USBEH4	I will almost certainly use Halodoc's consulting services with doctors again in the future.
Behavioral intention	BEHINT1	I am willing to use the Halodoc application.
	BEHINT2	I am open to using the Halodoc application.
	BEHINT3	I am interested in using Halodoc's consulting services.
	BEHINT4	I will continue to use the Halodoc app to communicate with doctors about my health for early health checks.
Performance Expectancy	PEX1	Halodoc's consultation services with doctors are helpful in determining my health status.
	PEX2	By utilizing Halodoc's doctor consultation services, I can improve the quality of my health.
	PEX3	Halodoc's doctor consultation services can assist me in protecting or maintaining my health.
	PEX4	Interacting with doctors through Halodoc services increases my self-awareness for health maintenance.
Effort Expectancy	EFEX1	I understand how to use Halodoc's doctor consultation service.
	EFEX2	It is clear how to use Halodoc's consultation service with a doctor.
	EFEX3	I am very comfortable using Halodoc's consultation services with doctors.
	EFEX4	Halodoc's doctor consultation services are simple to use
	EFEX5	If there are new features in the Halodoc application, I will not hesitate to learn about or test them.
Social Influence	SOINF1	Friends and colleagues in my network have recommended that I use the Halodoc application for health consultations.
	SOINF2	Even people close to me, such as family members, advise me to use the Halodoc application for health consultations.
	SOINF3	I would feel guilty if I didn't use the Halodoc app when people close to me or of significance were using it.
Attitude towards using technology	ATTUT1	Using Halodoc's consultation service with a doctor is a good idea.
	ATTUT2	Because doctors are available for consultations, Halodoc makes it easier to obtain health consultations.
	ATTUT3	Halodoc's doctor consultation services are beneficial to me.
	ATTUT4	I enjoy using Halodoc's doctor consultation services.
Facilitating Condition	FASC1	Because I'm afraid of getting infected if I go to the hospital, I rely on existing health apps.
	FASC2	I use health apps because they allow me to obtain health services (consultation, prescription, diagnosis) more quickly.
	FASC3	I only use health apps in emergencies.
	FASC4	I use health apps because they are less expensive.
	FASC5	I use the health application because I have experience working with the health and social security administration.
Perceived ease of use	PEREU1	Every feature of the Halodoc application is simple to use.
	PEREU2	It was very simple for me to learn how to use all of the Halodoc application's features.
	PEREU3	When it comes to using the Halodoc app to consult with doctors, I have no issues.
Perceived usefulness	PERFUL1	The Halodoc application will benefit my need for health checks.
	PERFUL2	The Halodoc application performs more health-care functions than I anticipated.
	PERFUL3	Halodoc's service, in my opinion, is effective for diagnosing patients.
	PERFUL4	The Halodoc application allows me to efficiently manage consultation scheduling.
	PERFUL5	The Halodoc application service makes it possible to exchange information about patient conditions.

4. Results and Discussion

4.1. Distribution of Participant Profiles

Table 2 shows the profile distribution of the participants in this study. Participants were divided into two groups based on their generation–Y or Z–which totaled 134. Furthermore, nearly 60% of the participants were female, with male participants accounting for nearly 44%. This study also explores the significance of using the Halodoc application. According to the participants' responses, personal gain was the dominant reason for use, by nearly 70%. Meanwhile, use for family purposes reached nearly 32%. Regarding the educational backgrounds of the app's users, the majority of participants (more than 85%) had earned undergraduate degrees, with smaller proportions having earned diplomas (more than 6%), high school or equivalent (almost 6%), or master's degrees (almost 3%). Furthermore, nearly 67% of the participants in this study were private employees, nearly 20% were homemakers, more than 6% were entrepreneurs, nearly 6% were professionals, and more than 2% were civil servants.

Table 2: Distribution of Participant Profile

Description		N	%
Age	29-43 years old (Gen Y)	134	50%
	Less than 29 years old (Gen Z)	134	50%
Gender	Female	151	56.34%
	Male	117	43.66%
Interest in using Halodoc	Personal interests	183	68.28%
	Family interests	85	31.72%
Educational background	High school / equivalent	15	5.60%
	Diploma	18	6.72%
	Bachelor	228	85.07%
	Master's degree	7	2.61%
Profession	Housewife	52	19.40%
	Private sector employee	179	66.79%
	Government employees	6	2.24%
	Professional	14	5.22%
	Entrepreneur	17	6.34%

The fit model in this study is based on the standardized root mean square (SRMR) value, which must be less than 0.1; the SRMR value of 0.07 indicates that this research model meets the data fit criteria. Table 3 displays the coefficient of determination results obtained by examining the R^2 results. The behavioral intention variable has an R^2 of 0.714, indicating that the variables of performance expectancy, effort expectancy, social influence, attitude toward using technology, facilitating conditions, perceived ease of use, and perceived usefulness account for 71.4% of the explanation. Meanwhile, the R^2 value of 0.132 for usage behavior indicates that 13.2% of the usage behavior variable is explained by performance expectancy, effort expectancy, social influence, attitude toward using technology, facilitating conditions, perceived ease of use, perceived usefulness, and behavioral intention.

Table 4 shows the results of this study's PLS algorithm. These findings describe several tests, including reliability and validity. This research measures reliability based on the CR test results; to be considered reliable, the CR results in this study must be greater than 0.7. All variables (performance expectancy, effort expectancy, social influence, attitude toward using technology, facilitating conditions, perceived ease of use, perceived usefulness, and behavioral intention) in this study show results above 0.7, and thus all variables are variable. The outer loading (OL) results in Figure 2—where each item's OL value must be greater than 0.7—also supported the study's reliability findings. Based on the results, each item of all variables has a value greater than 0.7, indicating that all variables are reliable. This study also examines CA results in the validity test; this value must be greater than 0.7. Based on the results, all variables have values greater than 0.7, indicating that all variables in this study are valid. The validity of this study is further determined by the AVE results, which must be greater than 0.5. Based on the results, all variables have values greater than 0.5, indicating that all variables in this study are valid. The validity of this study was also strengthened by examining the results of cross loadings (CL), which showed that the loading value for each measured indicator was greater than the loading value for the other constructs.

Table 3: Model fit and coefficient of determination

Description	Saturated model	R^2
SRMR	0.071	-
Behavioral intention	-	0.714
Usage behavior	-	0.132

Note: SRMR=Standardized Root Mean Square (<0.1)

4.2. Hypothesis Testing

Table 5 displays the results of the hypothesis testing in this study, which are based on the *p* value results (0.05). The hypothesis was tested over two generations in the study. In hypothesis 1a (H1a), the path of performance expectancy → behavioral intention has a *p* value of 0.343 (Gen Y) and 0.388 (Gen Z). Based on these findings, it is possible to explain why performance expectancy has no effect on behavioral intention in both the Y and Z generations. These findings demonstrate that H1A is rejected for both generations. Furthermore, the *p* values for H1b are 0.405 (Gen Y) and 0.391 (Gen Z). These findings explain why performance expectancy, as mediated by behavioral intention, has no effect on usage behavior; thus, H1B is rejected for generations Y and Z.

In addition, the *p* values for H2a are 0.587 and 0.943. These findings explain why, for both generations Y and Z, effort expectancy has no effect on behavioral intention. This study thus rejects H2A for both Gen Y and Gen Z. Meanwhile, effort expectancy mediated by behavioral intention has no significant mediating effect on usage behavior. This is evident from the *p* values of 0.627 and 0.944, indicating that H2b is rejected for both generations Y and Z in this study. On the path of social influence → behavioral intention has *p* values of 0.122 and 0.061, indicating that social influence has no significant effect on behavioral intention; hence, this study rejects H3a for the two generations studied. The *p* values for the mediation effect of social influence are 0.240 and 0.066. These findings explain why, for both Gen Y and Gen Z, social influence mediated by behavioral intention has no effect on usage behavior. Therefore, H3b is rejected.

The *p* values for H4a are 0.143 and 0.019. These findings explain a different phenomenon, in which Generation Y's attitudes toward technology have no significant effect on behavioral intention, ruling out H4a for Generation Y. Meanwhile, for Generation Z, these results confirm H4a. Furthermore, examining the mediating effect produces similar results, with *p* values of 0.197 and 0.023, respectively. These findings indicate that Generation Z's attitude toward technology, as mediated by behavioral intention, has a significant influence on usage behavior, and H4b is accepted for this generation. For Generation Y, H4b is rejected. The *p* values for H5a are 0.191 and 0.312, indicating that facilitating conditions have no significant effect on behavioral intention for either of the two generations in this study. These findings indicate that H5a is rejected for both generations.

In the sixth hypothesis, the path of perceived ease of use → behavioral intention yields *p* values of 0.419 and 0.045, for two different results. In the first result, the *p* value, explains that H6a is rejected for Generation Y; perceived ease of use has no significant effect on behavioral intention. Meanwhile, H6a is accepted for Generation Z. Regarding the mediating effect, results demonstrate that for Generation Z, perceived ease of use, as mediated by behavioral intention, significantly influences usage behavior, and H6b is accepted for this generation. For Generation Y, H6b is rejected.

The *p* values for the seventh hypothesis are respectively 0.002 and 0.000. These results indicate that perceived usefulness influences behavioral intention in both the Y and Z generations, and thus H7a is accepted for both generations. In terms of the mediating effect, the respective *p* values are 0.045 and 0.000, indicating that perceived usefulness mediated by behavioral intention significantly influences usage behavior for both generations, and H7b is accepted for both generations. Lastly, in H8, the respective *p* values are 0.003 and 0.000, indicating that behavioral intention for both generations Y and Z has a significant influence on usage behavior. Hence, H8 is accepted in this study for both generations.

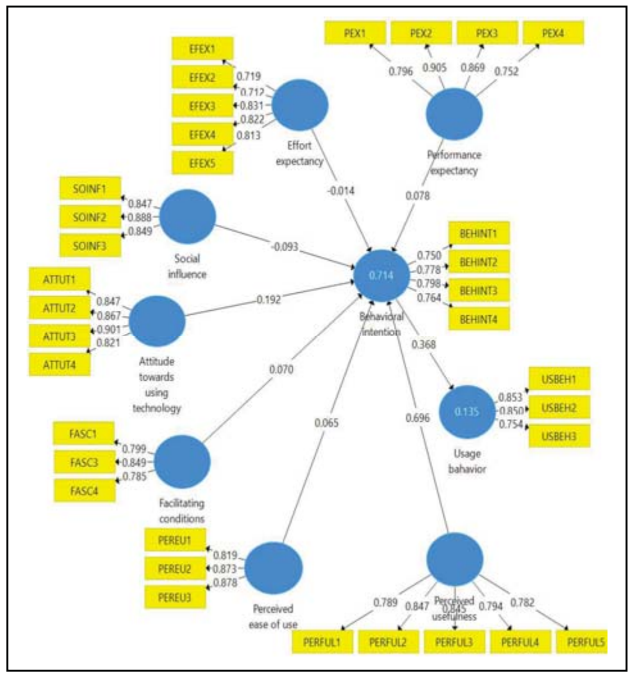

Figure 2: Outer loading

Table 4: PLS-Algorithm Measurement

Variable	CA	CR	AVE	Cross loadings								
				PEX	EFEX	SOINF	ATTUT	FASC	PEREU	PERFUL	BEHINT	USBEH
Performance expectancy	0.851	0.900	0.693	0.833	-	-	-	-	-	-	-	-
Effort expectancy	0.841	0.887	0.611	-	0.782	-	-	-	-	-	-	-
Social influence	0.827	0.896	0.743	-	-	0.862	-	-	-	-	-	-
Attitude towards using technology	0.882	0.919	0.739	-	-	-	0.859	-	-	-	-	-
Facilitating conditions	0.740	0.852	0.658	-	-	-	-	0.811	-	-	-	-
Perceived ease of use	0.819	0.892	0.735	-	-	-	-	-	0.857	-	-	-
Perceived usefulness	0.870	0.906	0.659	-	-	-	-	-	-	0.812	-	-
Behavioral intention	0.775	0.855	0.597	-	-	-	-	-	-	-	0.773	-
Usage behavior	0.759	0.860	0.673	-	-	-	-	-	-	-	-	0.820

Note: OL=Outer loading (>0.7); CA=Cronbach's alpha (>0.7); CR=Composite reliability (>0.7); AVE=Average variance extracted (>0.5); PEX = Performance expectancy*; EFEX=* Effort expectancy*; SOINF=* Social influence*; ATTUT=* Attitude towards using technology*; FASC=* Facilitating conditions*; PEREU=* Perceived ease of use*; PERFUL=* Perceived usefulness*; BEHINT=* Behavioral intention; USBEH= Usage behavior

Table 5: Hypothesis Testing

Hypothesis	Standard Deviation		T-Statistic		P Value		Remark	
	Gen Y	Gen Z	Gen Y	Gen Z	Gen Y	Gen Z	Gen Y	Gen Z
H1a	0.112	0.109	0.948	0.865	0.343	0.388	H1a rejected	H1a rejected
H1b	0.038	0.059	0.834	0.858	0.405	0.391	H1b rejected	H1b rejected
H2a	0.103	0.089	0.543	0.072	0.587	0.943	H2a rejected	H2a rejected
H2b	0.035	0.049	0.486	0.070	0.627	0.944	H2b rejected	H2b rejected
H3a	0.116	0.119	1.551	1.878	0.122	0.061	H3a rejected	H3a rejected
H3b	0.046	0.065	1.176	1.843	0.240	0.066	H3b rejected	H3b rejected
H4a	0.081	0.106	1.469	2.348	0.143	0.019	H4a rejected	H4a accepted
H4b	0.028	0.059	1.292	2.284	0.197	0.023	H4b rejected	H4b accepted
H5a	0.047	0.052	1.308	1.013	0.191	0.312	H5a rejected	H5a rejected
H5b	0.016	0.029	1.118	0.987	0.264	0.324	H5b rejected	H5b rejected
H6a	0.101	0.060	0.808	2.013	0.419	0.045	H6a rejected	H6a accepted
H6b	0.035	0.033	0.700	1.979	0.484	0.048	H6b rejected	H6b accepted
H7a	0.126	0.052	3.155	13.540	0.002	0.000	H7a accepted	H7b accepted
H7b	0.059	0.060	2.006	6.369	0.045	0.000	H7b accepted	H7b accepted
H8	0.102	0.069	2.941	7.787	0.003	0.000	H8 accepted	H8 accepted

4.3. Discussion

This study's results show that for both Generation Y and Generation Z, performance expectancy has no significant effect on behavioral intention. Moreover, this study shows the role of behavioral intention as a mediator of performance expectancy on usage behavior. In general, the research results are not in line with some prior results (Abbad, 2021; Alabdullah et al., 2020; Mengesha, 2020; van der Vaart et al., 2016). However, certain factors, such as the young age of users, can have impacts on attitudes and behaviors in using health service applications (Arfi, Nasr, Khvatova, et al., 2021). Another study by (Arfi, Nasr, Kondrateva, et al., 2021) has explained that performance expectancy does not affect attitudes toward or use of health service applications. These results further indicate that, although performance expectancy reflects the effectiveness of use (Hoque & Sorwar, 2017), in certain situations and under certain user criteria, this variable can play a less dominant role in encouraging attitudes and behaviors toward using health service applications. This is in line with the situation during the third year of the pandemic, in which the number of COVID-19 cases has decreased considerably, and health services related to this matter are already widely available, so that health services in the form of applications are merely options rather than priority needs.

Garavand et al. (2019) and Rahimi et al. (2018) argue that effort expectancy has a significant effect on behavior intention in general. However, the results of this study differ, finding no significant relationship between effort expectancy and behavioral intention regarding the two generations studied. Regarding effort expectation and attitude toward use, these two aspects influence each other. If urgency of need arises during a related time period, then effort expectancy plays a role. However, if the urgency of use loses its momentum, effort expectancy is no longer the dominant factor in determining the attitude and behavior of using health service applications, for both the younger and older generations. Shiferaw et al. (2021) also express this idea; in explaining attitudes and behaviors related to using health service applications, their results indicate the effort expectation factor does not always play a dominant role. As associated with user criteria in this study, this further strengthens the concept that the importance of using health services will also be based on the urgency of use as a form of emergency need in user behavior.

The long-running global pandemic has altered people's perceptions of the importance of using health services, including mobile apps. In a roundabout way, this forces service providers to offer users more than just new features (Christian & Justinius, 2021). This situation creates a sense of urgency in all age groups, and research published during the pandemic (Alabdullah et al., 2020; Dash et al., 2019) explores this phenomenon. However, as pandemic conditions begin to normalize and the number of COVID-19 cases begins to drop dramatically, this perception may gradually fade. People may become accustomed to pandemics and accept them as the norm. Applying the UTAUT model clarifies that the urgency of the need to use e-health applications during times when panic is formed in the community will dominate the attitudes and behaviors of those using such applications. In contrast, if the situation becomes normal and no longer creates a sense of urgency, social influence will no longer have a significant impact on the attitudes and behaviors of those who use the applications. This is further related to the findings of Sezgin et al. (2016) and Shiferaw et al. (2021), in which social factors can be insignificant in influencing the decision to use.

Generation Z is more open and sensitive to the use of applications, including healthcare applications, than Generation Y. Although, in general, the attitude of the user influences their behavioral intention regarding subsequent use, research findings tend to show that these two variables have a significant relationship (Dash et al., 2019; McKee et al., 2021; Shiferaw et al., 2021). However, as with most societal trends, the attitude with which users respond to a trend will be directly proportional to their long-term behavior. This attitude will be influenced if the trend weakens or disappears, including when new trends arise. This study has explored this trend during the third year of the COVID-19 pandemic and suggests that the decreasing number of cases forms a more normal situation. As a result, people may have become accustomed to the pandemic and believe that the current situation has improved. Thus, their approach to dealing with the pandemic is different. This distinction also holds true for generations Y and Z. This attitude remains present in Generation Z because mobile applications, including health service applications, are still integrated into this group's lifestyle. Even though it is no longer a frequent use, this generation believes that issues or previous experiences can influence user attitudes and long-term use behavior regarding the application. This is consistent with the viewpoint of Monthuy-Blanc et al. (2013), who argue that for some people, a viewpoint is simply a viewpoint that is not strong enough to elicit a desire take action.

A well-designed application's facilitating conditions reflect adequate infrastructure, technical capacities, and organizational capabilities for its use. This will have an impact on attitudes and behaviors in use (Alabdullah et al., 2020; Sezgin et al., 2016). This will become an important issue when health services coexist with a pandemic situation. During the current pandemic, the community, including generations Y and Z, demanded that the quality of health information and services provided be appropriate and reliable. As the number of existing cases has decreased significantly in the third year of the pandemic, the requirement for facilitating conditions in health service applications has become a smaller issue for the community. In the current context, an e-health application is more of a one-time requirement than an urgent, ongoing requirement. As a result, the perception of demands on facilitating conditions diminishes. This is consistent with the idea that there are times when people do not see the benefits as a factor influencing their intention to use (Shiferaw et al., 2021).

A newly released application will almost certainly pass the evaluation of its users. This rating reflects the application's ease of use. During the pandemic, healthcare applications like Halodoc had already launched and were widely known. Halodoc's use, however, is not as widespread as its popularity. Because of the pandemic, its popularity is directly proportional to its number of users. During this time, users will respond to the ease of use they encounter. Typically, Generation Z will find the Halodoc application simple to use, whereas this may not apply entirely to users of an older generation. As previously stated, people, particularly young users, will want to use an application if they believe it is simple to use (Christian, Indriyarti, et al., 2022). Because the perceived ease of use affects the desire to use an application, complex usage will present an individual barrier to (Christian & Agung, 2020; Veríssimo, 2018; Yee et al., 2019). This convenience of use can be reflected in an application's ease of navigation or features available (Susanto & Aljoza, 2015).

Health is fundamental to the community, including generations Y and Z. Even though the pandemic has begun to improve, and the situation has begun to return to normal, health services remain a community need. As a result, the presence of health service applications is still regarded as a community benefit, even if their use is not as extensive as it was during the first and second years of the pandemic. This is consistent with the belief that using health service applications will be beneficial and fulfill needs, resulting in a favorable attitude toward their use (Lee, 2018; Morosan & DeFranco, 2016; Vahdat et al., 2020). In everyday life, an application's efficacy, productivity, and high performance can indicate that the user finds the application useful (Yee et al., 2019). According to this study, both generations Y and Z generations believe that the presence of health service applications such as Halodoc can encourage attitudes and behaviors for future use.

In summary, perceived usefulness factors can shape attitudes and usage behaviors among users of health service applications in generations Y and Z. This is consistent with the findings of Garavand et al. (2019), Hoque and Bao, (2015), and Venugopal et al. (2019), who demonstrate a link between attitudes and subsequent usage behavior. A strong desire to use an application can be a motivator to use it.

5. Conclusions

Based on the findings presented above, this study has an intriguing distribution of conclusions. First, generations Y and Z do not see a link between performance expectancy and behavioral intention, even when behavioral intention is used as a mediator. Second, this study aligns with previous findings related to the second hypothesis: this research indicates that effort expectancy for the two generations studied has no significant effect on their behavioral intention. This is also true for the mediated effect. Third, the findings of this study show that social influence is not considered to have a significant impact on behavioral intention among generation Y and Z users. Similarly, even when behavioral intention is used as a moderator, the results are insignificant. This study also explains the differences in results between the two generations. In Generation Y, behavioral intention has no bearing on attitude toward using technology, and the results remain the same if behavioral intention is used as a mediator for usage behavior. However, when applied to Generation Z, the findings stand in contrast. These findings support the notion that Generation Z's attitudes and behaviors toward technology are more open and sensitive, allowing them to easily switch between applications.

The fifth result of this study explains that the concept of facilitating conditions for behavioral intention is not significant to either of the two generations in this research. Similarly, when behavioral intention acts as a moderating variable for usage behavior, the indirect effect occurs. The sixth finding of this study emphasizes that Generation Z users of the Halodoc application see a significant relationship between their perceived ease of use and behavioral intention. This remains the case for Generation Z if behavioral intention is used as a moderator of usage behavior. The findings differ for Generation Y, for whom the relationship between these variables, both directly and indirectly, is not significant. The seventh finding describes how perceived usefulness influences behavioral intention in both generations Y and Z. The same is true for the indirect effect when behavioral intention is used as a mediator for usage behavior. The study's results show that behavioral intention has a significant influence on usage behavior across both generations.

5.1. Theoretical Implications

Even in health care applications, the UTAUT model is seen as a good way to measure how well a new technology is adopted or accepted. However, special situations, such as when they begin breeding or after a pandemic, must be studied because many factors may be insignificant. This demonstrates that using health services when they are most needed will almost certainly demonstrate the importance of all variables in the model. However, during the third period of the pandemic, the utility variable continued to play a dominant role in explaining the significance of attitudes and behaviors in using these services. When the urgency of use is formed in terms of a compelling situation such as a pandemic, other variables such as performance expectancy, effort expectancy, social influence, and facilitating conditions appear to play a greater role. Surprisingly, this UTAUT model will demonstrate the possibility of different outcomes for different generations of healthcare app users. This is significant as a supplement to the theoretical implications, particularly in the concept of technology adoption behavior models, where different situations and generations can have varying influences.

The next implication, which is also the research's value, is the advancement of the concept of central place theory. This theory, as is widely known, emphasizes that it is closely related to areas or distribution networks such as large cities in terms of the distribution of goods and services. According to this study, the distribution of e-health services in major cities such as Jakarta will be influenced by behavior toward perceived usefulness for generation Y, while it will be more diverse for generation Z. Based on this theory, we will be able to determine more appropriate target users by considering the benefits of an e-health service.

5.2. Practical Implications

This study adds to the practical implications of health care providers needing to be better prepared to deal with changing perspectives of health care application users. This service is deemed important and necessary, but there is a sense of urgency and an underlying need. As a result, once the pandemic situation has stabilized, the variables that shape the attitude and behavior of those who use the application must be adjusted to a set of marketing strategies and approaches. Emphasizing usefulness factors in advertisements, for example (Girsang et al., 2022; Yulita et al., 2022), can be one of the keys to selling this service to the general public, particularly users from generations Y and Z.

5.3. Limitations of The Study and Recommendation Future Research

This study does have some limitations. First, even though this study compared two generations (Y and Z), it feels necessary to include generation X (born 1965-1980) in revealing more details about attitudes and behavior in using health service applications. Some generations from generation X may become users of health service applications, regardless of whether that generation is in a disease-risk health status. Furthermore, the third year is used as a research period in this study because Indonesia and possibly other countries have not yet declared themselves fully free of COVID-19. As a result, the year in which the government declared that it was free of the pandemic felt the need to be used as a study period for additional research. Although the study's sample size is relatively large, the distribution of different regions of a country is required to better represent the generalization of the research area.

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