

Understanding the Determinants of m-Health Adoption in Indonesia

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Abstract

Objective: Mobile health (m-health) is a fast-growing service that enables users to consult with doctors remotely. This research investigates the factors influencing m-health adoption in Indonesia using The Unified Theory of Acceptance and Use of Technology (UTAUT).

Design/Methods/Approach: A quantitative method was applied by distributing an online questionnaire to active users of the m-health application in Greater Jakarta. The data from 242 respondents was collected through non-probability sampling techniques and analyzed by Structural Equation Modeling (SEM).

Findings: The findings show that performance expectancy and price value have significant positive effects on behavioural intention. Behavioural intention significantly encourages actual usage behaviour of m-health services among consumers.

Originality: This study discusses the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) mobile health application in the Indonesian market and adds a perceived risk variable to the model to determine the influence of this variable on behavioural intention in the Indonesian context.

Practical/Policy implication (optional): The findings of this research offer recommendation for m-health service providers regarding health service and the fit value of consumers.

Keywords: m-Health, Performance, UTAUT, Value

JEL Classification: M31, O33



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JURNAL MANAJEMEN
TEORI DAN TERAPAN

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I. Introduction

Developments in information and communication technology occur rapidly and encourage the health industry to expand access to health services. Various services have emerged, such as e-health, telemedicine, and telehealth. Mobile health (m-health) has rapidly evolved (Lee & Han, 2015). The m-health service is a part of the development of e-health services available on mobile media (Deng, Mo, & Liu, 2014). Health services through smartphones allow users to access health services interactively and personally without being limited by time and place (Deng et al., 2014) and are easy to reach (Post, 2021). In limited mobility, the application of digital health services becomes a solution for people who are hesitant to seek face-to-face consultations (Cheng et al., 2021). The results of research conducted by Nielsen on September 20 showed that there are 47% of active users of digital health service applications in Indonesia.

Studies about the factors influencing m-health adoption have been performed but are very limited, such as the analysis of senior users in Bangladesh (Venkatesh et al., 2008; Moudud-UI-Huq et al., 2021) and customer-producer relationships (Ake & Arcand, 2020). Other previous studies analyze price value and perceived reliability (Alam, Hoque, & Kaium, 2019) and the perceived risk of using m-health (Yin, Li, & Qiao, 2016). Another study is limited to a literature review (Aljohani, Nasser; Chandran, 2021) or several countries (Alam, Hoque, & Kaium, 2019). Nevertheless, a study that involves both perceived quality and perceived risk would be interesting to get comprehensive insight. The Unified Theory of Acceptance and Use of Technology (UTAUT) has commonly been used for research regarding technology adoption in health-related industries regarding several aspects, such as cost and interaction aspects (Maleka & Matli, 2022), situational challenges and health concerns (Barua & Barua, 2021), customer attitude and condition (Donmez-Turan, 2020). However, those studies were not done explicitly for m-health users and were only conducted in Bangladesh and Turkey. Considering the limitation of the extant studies of m-health technology adoption, the researchers seek to examine the influence of some customers' perceptions on behavioral intention in the Indonesian context as a potential and emerging country with the 4th largest population in the world.

This research uses the quantitative research method to analyze the effect of performance expectancy, effort expectancy, social influence, facilitating condition, and price value on behavioural intention. In addition, the research conducted also analyzes the effect of perceived reliability and perceived risk on behavioural intention and examines the effect of behavioural intention on actual usage behaviour using m-health services. The study was conducted on HD application users who live in Greater Jakarta.

This study offers several contributions. First, it extends UTAUT in m-health technology, which is relatively new in Indonesia. Second, it identifies important factors of Indonesian consumers' perceptions to accelerate technology adoption during the pandemic. Third, understanding the determinants of m-health technology adoption is beneficial for leveraging the effectiveness of m-health services in the future. Finally, the findings provide guidelines for service providers, policymakers, and healthcare organizations to create a comprehensive view and optimize m-health benefits.

This manuscript is opened with a description of the previous research findings and the importance of conducting this research. Next, the literature review on the theory and hypothesis development was elaborated as the research model's fundamental. Furthermore, the research method was explained, and data was collected and analyzed. Finally, a discussion of the research findings was elaborated to get conclusions on hypothesis testing.

2. Literature Review and Hypotheses Development

2.1 *The unified theory of acceptance and use of technology (UTAUT)*

The essence of UTAUT underlies the intention of information technology as the driver of actual usage (Philippi et al., 2021). Understanding individual acceptance of new technology is a common topic of study within the information systems literature (Hu et al., 1999). The results of previous research regarding UTAUT demonstrate several approaches to use in the context of individuals, organizations, and technology (Davis, 1989) as well as macroeconomics (Taylor & Todd, 1995). However, researchers often ignore the contribution of alternative research models (Venkatesh et al., 2003).

Venkatesh et al. (2003) formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) model by reviewing theoretical models: The theory of Reasoned Action (Fishbein and Ajzen, 1975), the Technology Acceptance Model (Davis, 1989), the Motivational Model (Davis et al., 1992), Theory of Planned Behavior (Ajzen, 1991), combination Theory of Reason Action and Theory Plan Behavior (Taylor dan Todd, 1995), Model of PC Utilization (Thompson et al., 1991), Innovation Diffusion Theory (Rogers, 2004), and Social Cognitive Theory (Bandura, 2014). Each construct in these eight theoretical models was tested. The results showed that four constructs significantly influenced acceptance and actual usage behavior: performance expectancy, social influence, effort expectancy, and facilitating condition (Venkatesh et al., 2003). Sabbir et al. (2020) explained that the acceptance of innovative technology is influenced by individual characteristics (effort expectancy and performance expectancy) as well as organizational (facilitating condition) and social influence.

2.2 Performance expectancy and behavioral intention

Performance expectancy refers to the perception of trust to achieve job performance using technology (Venkatesh et al., 2003). Five constructs derived from the various models are used, including perceived usefulness, extrinsic motivation, job fit, relative advantage, and outcome expectations that have been developed through several studies (Davis, 1989; Davis, Bagozzi, & Warshaw, 1992; Thompson, Higgins, & Howell, 1991; Moore & Benbasat, 1991; Compeau & Higgins, 1995). If a mode of technology provides convenience in everyday life, users are more motivated to accept and utilize it (Alalwan, Dwivedi, & Rana, 2017; Sivathanu, 2018). The usefulness and ability of m-health to fulfill the user's needs drive the intention to use it (Venkatesh et al., 2012; Alam et al., 2019). The desire to use m-health is also driven by its convenience to use it anytime and anywhere (Ben Arfi et al., 2021; Dwivedi et al., 2016; Yin et al., 2016). Hoque and Sorwar (2017) stated that performance expectancy drives patients' intention to use m-health services. Similar findings are also shown in other studies (Alam et al., 2021) and refer to the following hypothesis.

Hypothesis 1: Performance expectancy positively influences behavioral intention to use m-health.

2.3 Effort expectancy and behavioral intention

Effort expectancy is the belief that a system will be easy to use and require little effort (Venkatesh et al., 2003; Alam et al., 2019). Users who make less effort to understand and use an application increase its usage possibility (Venkatesh et al., 2003; Donmez-Turan, 2020). Desire to use an application also emerges when consumers are happy to use new technology that is easy and comfortable to use (Alalwan et al., 2017; Shareef et al., 2017). According to Sun et al. (2013), Donmez-Turan (2020), and Wang et al. (2017), effort expectancy is the main attribute in influencing the intention to use a service application. Thus, the second hypothesis was proposed as follows:

Hypothesis 2: Effort expectancy positively influences behavioral intention to use m-health

2.4 Social influence and behavioral intention

Social influence refers to the encouragement given to someone using a new system (Venkatesh et al., 2003). Social influence includes subjective norms, social experiences, and images (Venkatesh et al., 2003; Izuagbe & Popoola, 2017). Although the terms of each construct differ, some concepts show that behavior is influenced by the beliefs of others when using technology (Venkatesh et al., 2003). In the context of technology acceptance, a person's actions tend to be based on social interactions with others, such as friends and family (Ratten, 2015). Social influence has a significant effect on the intention to purchase online (Soh et al., 2020) and the intention to use technology-based health information such as m-health (Alam et al., 2020b) and e-health (Boontarig et al., 2012). Therefore, the following hypothesis is determined.

Hypothesis 3: Social influence positively influences behavioral intention to use m-health.

2.5 Facilitating condition and behavioral intention

A facilitating condition refers to the supporting infrastructure that affects potential users through convenience in dealing with a system (Venkatesh et al., 2003). Facilitating conditions such as the availability of gadgets or internet connections enable consumers to use new technology. Facilitating condition determines the user's perception of behavior (Tam, Santos, & Oliveira, 2020). In the context of mobile applications, the more conducive the facilitating condition in an application, the higher the possibility for people to use the application (Tam et al., 2020, Boontarig et al. (2012) stated that facilitating conditions drive the intention to use smartphones to access health services. A facilitating condition has a significant influence on the intention to use m-health services (Dwivedi et al., 2016). Therefore, the following hypothesis is:

Hypothesis 4: A facilitating condition positively influences behavioral intention to use m-health.

2.6 Perceived reliability and behavioral intention

Perceived reliability is the perception of consumer confidence in a new technology that can work consistently and accurately (Lee, Lee, & Eastwood., 2003). According to Alam et al. (2020b), perceived reliability drives users to believe in the technology that functions as promised by the service provider (Alam et al., 2020b). If a friendly system is used, users will feel that the technology is reliable and trustworthy (Alam et al., 2020b). In the context of medicine and health products, perceived reliability is a major factor in influencing consumers' intentions to buy medicine online (Yin et al., 2016). Perceived reliability affects behavioral intention toward actual usage behavior on mobile-based technology (Sharma & Sharma, 2019). The higher the perceived reliability, the higher the intention to buy medicine on the Internet (Yin et al., 2016), so the hypothesis of this study is as follows:

Hypothesis 5: Perceived reliability positively influences behavioral intention to use m-health.

2.7 Perceived risk and behavioral intention

Perceived risk is the perception of subjective feelings of uncertainty with using new services or technologies (Yin et al., 2016). Another definition provided by Wissal et al. (2021) is an erratic action in one's behavior during which the user believes that there are negative consequences for a product/service (Natarajan, Balasubramanian, & Kasilingam,

2017). The higher the perceived risk, the more consumers will use conventional methods to buy products/services (Aref & Okasha, 2020). The decision to use digital services tends to be more complex because it builds long-term relationships between consumers and service providers (Featherman & Pavlou, 2003). When using digital services, one avoids losses to get the expected results (Ben Arfi et al., 2021). Previous studies have found that high perceived risk affects the intention to use health service applications especially (Ben Arfi et al. (2021). Therefore, the following hypothesis is determined:

Hypothesis 6: Perceived risk negatively influences behavioral intention to use m-health.

2.8 Price value and behavioral intention

The price value is the cognitive value according to consumer perceptions used to compare the new system's financial benefits and costs (Venkatesh, Thong, & Xu, 2012). Price value indicates the level of the price received and the best value to be paid (Sweeney & Soutar, 2001). For consumers, price is an important factor related to the costs incurred (Dodds, Monroe, & Grewal, 1991). In marketing research, price is generally related to product/service quality (Zeithaml, 1988). Technology users compare the prices and discounts obtained from continuous use (Alam et al., 2020b). Rationale and logic drive people to decide to use or refuse service. In this case, a delicate balance exists between the costs and benefits obtained from a service (Baabdullah, 2018). In the context of mobile technology, Karaiskos et al. (2009) indicated that price value significantly drives the intention to use mobile services. Thus, the hypothesis formulation is as follows: Hypothesis 7: Price value positively influences behavioral intention to use m-health.

2.9 Behavioral intention and actual usage behavior

Previous studies show that intention and behavior have a strong relationship regarding technology acceptance (Kijisanayotin, Pannarunothai, & Speedie, 2009). Behavioral intention significantly influences and demonstrates a direct effect on the actual usage behavior of using m-health services (Venkatesh et al., 2003). Behavioral intention shows the readiness of a user to engage in actual action. It drives and convinces someone to use mHealth during the pandemic when people were urged to engage in social distancing. Behavior intention becomes the predictor for actual usage behavior (Alam et al., 2021). Thus, the hypothesis formulation is:

Hypothesis 8: Behavioral intention positively influences actual user behavior to use m-health.

3. Method

Conclusive descriptive research is a quantitative research design with the main objective of describing the relationship between variables (Malhotra, 2019). The population in this study comprises m-health service users in Indonesia, and the sample includes m-health service users who live in the Greater Jakarta area. The number of m-health users in Indonesia is quite high, with more than 15 million people after the COVID-19 pandemic in 2022 (<https://www.kominfo.go.id/>). Furthermore, HD was founded in Jakarta in 2016 and 2022 and has reached other big cities in Indonesia (<https://www.HD.com/>). Generally, the number of samples requires at least five times the number of research indicators (Hair et al., 2006). Consequently, the minimum sample size is at least 195 respondents, which includes five of each of the 39 indicators in this research.

Non-probability sampling was applied using convenience and snowball sampling. Initially, the authors contacted some recognized respondents who use m-health regularly. Then, after they answered the questionnaire, we asked them to distribute the questionnaire link to their relatives or friends. Data were collected through an online survey technique using an online form questionnaire in 2021. The questionnaire was distributed on various social media such as Line, WhatsApp, Instagram, and Telegram. The data collected was checked and went through data cleaning. A validity and reliability test were performed before the clean data were finally processed and analyzed with Equation Structural Modeling (SEM) using Lisrel 9.3.

This quantitative research develops instruments containing measurement variables that describe the tested factors. The measurement of each indicator that measures a variable in a particular construct uses a Likert 5-point scale, where one indicates strongly disagree, and five strongly agree (see Table 1).

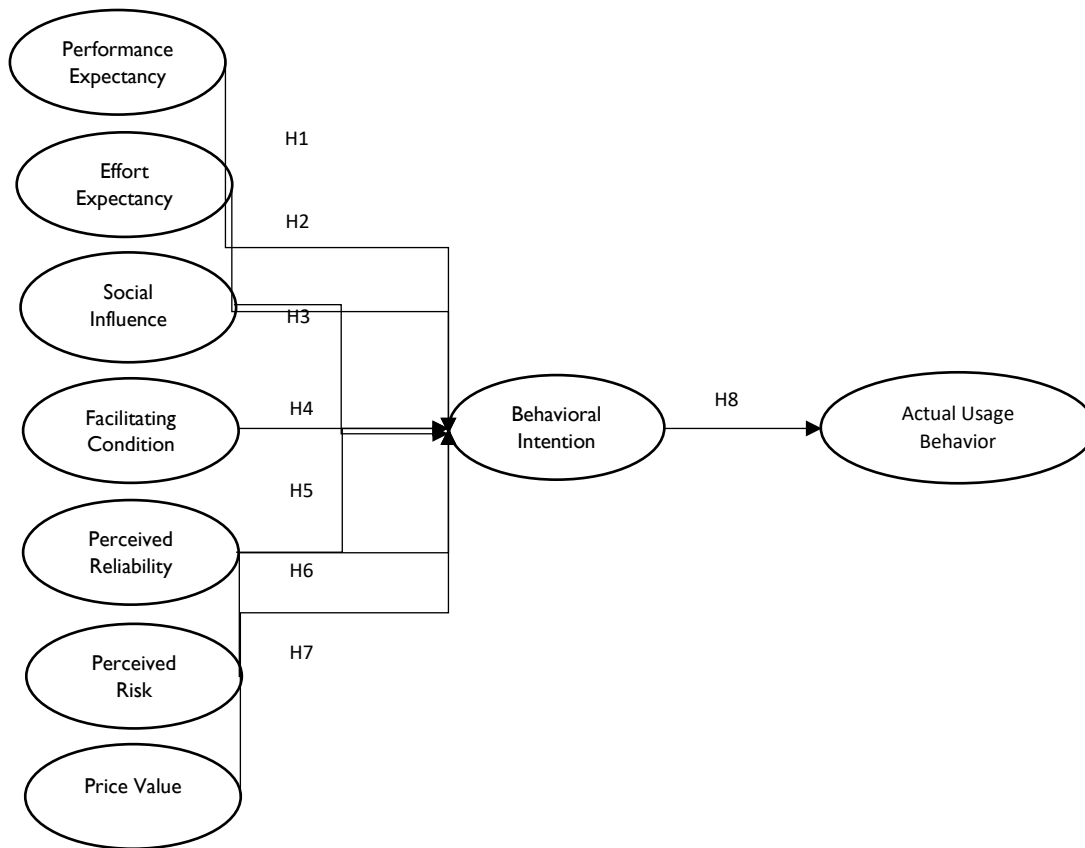


Figure 1. Research Model

Table 1. Instrument development

Construct	Definition	Indicators	Source
Performance Expectancy	The perception of trust to achieve job performance by using technology	I find HD useful in my life. (PE1)	Venkatesh et al. (2012); Alam et al (2019)
		Using HD increases my chances of fulfilling my needs. (PE2)	Venkatesh et al. (2012); Alam et al (2019)
		Using HD saves my time. (PE3)	Ben Arfi et al. (2021)
		I can use HD anywhere. (PE4)	Ben Arfi et al. (2021)
		Using HD helps me accomplish my daily tasks more quickly. (PE5)	Dwivedi et al. (2016)
		I feel that using HD is convenient for me. (PE6)	Yin et al. (2016)
Effort Expectancy	The belief that a system will be easy to use and require little effort	I know how to purchase using HD. (EE1)	Venkatesh et al. (2003); Alam et al (2019)
		I find HD is easy to use. (EE2)	Venkatesh et al. (2003); Sabbir, Islam, & Das (2020)
		My interaction with HD is clear and understandable. (EE3)	Venkatesh et al. (2003); Alam et al (2019)
		I find HD as a flexible tool to interact with. (EE4)	Sok et al. (2011)
Social Influence	Encouragement is given to someone using a new system	My family thinks that I should use HD. (SI1)	Venkatesh et al. (2012)
		My friends suggest that I should use HD. (SI2)	Sok et al. (2011)

		Most people around me use HD for their health needs. (SI 3)	Ben Arfi et al. (2021)
Facilitating Condition	The supporting infrastructure that affects potential users through convenience in dealing with a system	HD is compatible with other technologies I use. (FC1)	Venkatesh et al. (2003); Venkatesh et al. (2012)
		Guidance will be available to me in the use of HD services. (FC2)	Venkatesh et al. (2012)
		All contents of HD are easy to read and understand. (FC3)	Sok et al. (2011)
		The information in HD is easily understood. (FC4)	Sok et al. (2011)
Perceived Reliability	The perception of consumer confidence in the new technology that can work consistently and accurately	Purchasing medicine in HD is trustworthy. (PR1)	Koufaris dan Hampton-Sosa (2004); Sabbir et al. (2020)
		I can rely on the services provided by HD. (PR2)	Gunawardana dan Perera (2015); Alam et al. (2019)
Perceived Risk	The perception of subjective feelings of uncertainty about using new services or technologies	HD is consistent over time. (PR3)	Alam et al. (2019)
		I am afraid that medicines from HD are harmful to my health. (RK 1)	Sabbir et al. (2020)
		I am worried about the quality of the medicine purchased online. (RK 2)	Sabbir et al. (2020)
Price Value	The cognitive value on consumer perceptions to compare the financial benefits and costs of using the new system	Using HD presents a big risk. (RK 3)	Yin et al. (2016)
		HD provides for my need at a reasonable price. (PV1)	Venkatesh et al. (2012); Alam et al. (2019)
		At the current price, HD provides a good value. (PV2)	Venkatesh et al. (2012); Alam et al. (2019)
Behavioral Intention	The level of consumers' intention to perform a certain behavior	At a price shown, HD is very economical. (PV3)	Dodds et al. (1991)
		I will always try to use HD when I need continuous service from medical professionals. (BI1)	Dwivedi et al. (2016)
		I will always try to use HD routinely. (BI2)	Venkatesh et al. (2012); Alam et al. (2019)
Actual Usage Behavior	Consumers' actual response	I am interested in HD systems. (BI3)	Sivathanu (2018)
		HD service is a pleasant experience. (AU1)	Alam et al. (2019)
		I want to use HD services to keep my health well. (AU2)	Alam et al. (2019)
		I will always try to use HD in my daily life. (AU3)	Alam et al. (2020a)

4. Result and Discussion

The total data collected was 279 that went through data cleaning. The outliers and incomplete data were removed, and finally, 242 data sets were selected to be processed with IBM SPSS Statistics to get descriptive profiles of respondents. Afterward, Lisrel 9.3 was used to test the hypothesis.

4.1 Results

This study involved 242 respondents with the characteristic described in Table 2. In general, users have used the HD application for the last three months until more than one year. Users are dominated by women who live in Jakarta and Tangerang. The age of active users ranges from 21-25 years, which are students, employees, and employers. The average income in one month varies from IDR 1,000,000 to above 5,000,000

Table 2. Respondents' profiles

Description	Number of Respondents	Percentage
Gender		
Male	80	33%
Female	162	67%
Age		
17-20	63	26%
21-25	109	45%
26-30	24	10%
31-35	17	7%
> 35	29	12%
Occupation		
Student	124	51.20%
Employee	80	33,1%
Employer	26	10,7%
Housewife	8	3,3%
Others	4	1,7%
Domicile		
Jakarta	129	53%
Bogor	15	6,2%
Depok	10	4,1%
Tangerang	74	30,6%
Bekasi	14	5,8%
Period of usage		
< 3 months	81	33,5%
3 - 6 months	38	15,7%
6 months - 1 year	43	17,8%
> 1 year	80	33%
The average income in one month (IDR)		
< 1.000.000	41	16,9%
1.000.000 - 2.999.999	53	21,9%
3.000.000 - 4.999.999	57	23,5%
≥ 5.000.000	91	37,6%

Confirmatory Factor Analysis (CFA) was conducted to ensure that the indicators properly measure the specific variable. The goodness of fit and hypothesis tests were performed using Structural Equation Modeling (SEM). According to Maholtra (2019), construct validity consists of convergent and discriminant validity. Convergent validity aims to show a positive correlation between one variable and another in the same construct. The acceptable measurement of convergent validity is indicated by the factor loading value of more than 0.5. Another measurement can be done by calculating the average variance extracted (AVE) value, which shows the variation among the latent construct with a value above 0.5.

A convergent validity test is done by looking at the factor loading. Overall, all indicators have a value above 0.5, with the highest value of factor loadings at 0.89 (Table 3). The AVE value on discriminant validity also shows good values of more than 0.5 (Table 3). The researcher follows the Three-Indicator Rule, which states that a good construct consists of at least three questions (Hair et al., 2019). Discriminant validity shows that one construct is truly distinct from other constructs. One observed variable represents only one latent construct. Cross-loading indicates that discriminant validity has a low difference, so the cross-loading value received is close to zero (Maholtra, 2019). Discriminant validity is proven if the square root of the AVE is greater than the correlation between constructs (Hair, Page, & Brunsveld, 2019). The discriminant validity test shows that, in general, the square root of the AVE value is higher than the correlation between constructs, so this test provides evidence of good discriminant validity (Table 4).

Table 3. Convergent validity and reliability

Construct and Indicator	Standardized Factor Loadings	Error	CR	AVE
Performance Expectancy (PE)			0.88	0.55
PE1	0.79	0.38		
PE2	0.73	0.46		
PE3	0.68	0.54		
PE4	0.74	0.45		
PE5	0.69	0.52		
PE6	0.82	0.33		
Effort Expectancy (EE)			0.84	0.64
EE1	0.64	0.59		
EE2	0.83	0.30		
EE3	0.91	0.18		
Social Influence (SI)			0.76	0.52
SI1	0.66	0.57		
SI2	0.76	0.42		
SI3	0.74	0.45		
Facilitating Condition (FC)			0.84	0.57
FC1	0.60	0.65		
FC2	0.73	0.47		
FC3	0.83	0.32		
FC4	0.85	0.28		
Perceived Reliability (PR)			0.80	0.58
PR1	0.66	0.57		
PR2	0.87	0.25		
PR3	0.74	0.45		
Perceived Risk (RK)			0.88	0.71
RK1	0.87	0.24		
RK2	0.89	0.20		
RK3	0.75	0.43		
Price Value (PV)			0.89	0.72
PV1	0.83	0.32		
PV2	0.86	0.26		
PV3	0.86	0.26		
Behavioral Intention (BI)			0.82	0.61
BI1	0.67	0.55		
BI2	0.79	0.37		
BI3	0.87	0.25		
Actual Usage Behavioral (AU)			0.90	0.75
AU1	0.83	0.31		
AU2	0.87	0.24		
AU3	0.89	0.21		

The reliability test measures the internal consistency of the variable indicators of a latent construct value (Hair et al., 2014). The reliability test was measured using composite reliability (CR) with a rule of thumb of at least 0.7, which indicates a reliable construct. A reliability value ranging from 0.6 to 0.7 is still acceptable, showing good validity indicators of a model's construct (Hair et al., 2014). In the reliability test, the composite reliability value of each construct ranges from 0.76 to 0.90 (Table 3), where a CR value of more than 0.6 indicates that the indicators of a model's construct validity are good (Hair et al., 2014).

Table 4. Discriminant validity

	BI	AU	PE	EE	SI	FC	PR	RK	PV
BI	<i>0.781</i>								
AU	0.964	<i>0.866</i>							
PE	0.769	0.741	<i>0.742</i>						
EE	0.523	0.505	0.726	<i>0.800</i>					
SI	0.458	0.442	0.517	0.295	<i>0.721</i>				
FC	0.595	0.574	0.800	0.785	0.401	<i>0.755</i>			
PR	0.715	0.690	0.900	0.737	0.490	0.780	<i>0.762</i>		
RK	0.129	-0.124	-0.200	-0.235	0.184	-0.276	-0.143	<i>0.843</i>	
PV	0.652	0.629	0.618	0.487	0.394	0.527	0.592	-0.010	<i>0,849</i>

Notes: The score in the diagonal space with italics is the square root of AVE

In this study, hypothesis testing was performed by Structural Equation Modeling (SEM) using LISREL 9.3. SEM is a combination of dependent-interdependent techniques consisting of two multivariate techniques: multiple regression and factor analysis (Hair et al., 2019). SEM aims to confirm the relationship directly or indirectly and accept or reject the proposed hypothesis. SEM requires a two-step analysis of measurement and structural models (Hair et al., 2019). The measurement model is used to specify the indicators that correspond to the latent construct and construct validity (Hair et al., 2019). In testing the measurement model, the goodness of fit (GOF) is used to determine the similarities between the researcher's theory (estimated covariance matrix) and reality (observed covariance matrix). The closer the values of the two matrices are, the more fit the model is declared (Hair et al., 2014). The measurement model analysis was followed by the structural model analysis, which aims to link the hypothesized model's constructs both correlational and dependently. The accepted hypothesis has a t-value above 1.96 (Hair et al., 2019). If the measurement model is fit, the next step is to test the structural model. The researcher compared the fit values on the measurement model and the structural model. The requirements for measuring fit are a small chi-square (χ^2/df), one absolute fit measure, and one incremental fit measure. The model has a value of χ^2/df that meets the criteria of less than 3 (Aggelidis & Chatzoglou, 2009) with an χ^2 value of 768.11 and a degree of freedom (df) value of 397. The structural measurement shows that the model has the goodness of fit indicators (Chi-square = 768.11; RMSEA = 0.062; RMR = 0.0335; CFI = 0.924; NNFI=0.911; IFI=0.925 and PNFI = 0.732) (Table 5). GFI, NFI, and RFI have values between 0.7 - 0.9, so they can be declared as having a marginal fit (Hair et al., 2010).

Table 5. The goodness of fit

The Goodness of Fit Indices	Standard	SEM	Description
Absolute Fit Indices			
χ^2/df	< 3	2.121	Good Fit
GFI	$\geq 0,9$	0.840	Moderate Fit
RMSEA	< 0,08	0.0622	Good Fit
RMR	< 0,1	0.0335	Good Fit
Incremental Fit Indices			
NFI	$\geq 0,9$	0.857	Moderate Fit
IFI	$\geq 0,9$	0.925	Good Fit
CFI	$\geq 0,9$	0.924	Good Fit
Parsimony Fit Indices			
PNFI	Relatively high values, better fit	0.732	Good Fit

The hypothesis is supported if the t value equals or exceeds 1.96. Then the direction of influence is indicated by the standard coefficient, whether positive or negative (Hair et al., 2019). The findings of the hypothesis test show that H1, H7, and H8 are accepted, while H2, H3, H4, H5, and H6 are rejected.

Table 6. Result of the hypothesis testing

Hypothesis	Standardized Coefficients (β)	t-value (critical ratio)	Result*
H1: PE \rightarrow BI	0.55	2.83	Supported
H2: EE \rightarrow BI	-0.09	-0.94	Not Supported
H3: SI \rightarrow BI	0.06	0.80	Not Supported
H4: FC \rightarrow BI	-0.06	-0.57	Not Supported
H5: PR \rightarrow BI	0.13	0.74	Not Supported

H6: RK → BI	-0.05	-0.82	Not Supported
H7: PV → BI	0.29	4.18	Supported
H8: BI → AU	0.96	11.24	Supported

*) Hypothesis is supported if the t-value is more than 1.96

4.2 Discussion

The results show that performance expectancy and price value are the only predictors with a positive effect on the behavioral intention of HD application users in the greater Jakarta area in Indonesia. Behavioral intention shows a significant influence on the actual usage behavior of using the m-health service.

The first hypothesis describes the influence of **performance expectancy on behavioral intention**. The hypothesis test results show that performance expectancy has a significantly positive effect on the behavioral intention of the HD application. Based on the results, HD application users feel that the service can greatly save their time for consultations with doctors instead of face-to-face. HD is perceived to give benefits and fulfill users' needs. It can save time and provide solutions comfortably instead of visiting the doctor directly and physically, especially during the pandemic. This finding is supported by Alam et al. (2020a), Yin et al. (2016), and Alam et al. (2020b), who explain that digital health services are useful and can increase the productivity of loyal users, thereby increasing their use.

The second hypothesis explains the influence of effort expectancy on behavioral intention. The test result shows that effort expectancy does not significantly affect the users of HD. This finding could be related to the profiles of the respondents, who are predominantly young people between the ages of 17 and 30. By nature, they are technology savvy, are familiar with the application in their daily practice, and automatically show intention to use it with less effort (Szymkowiak et al., 2021). The previous research showed a similar result (Alam et al., 2019; Alam et al., 2020a; Alam et al., 2020b) that behavioral intention to use m-health was not significantly influenced by effort expectancy.

The third hypothesis explains the effect of social influence on behavioral intention. The test results show that social influence from friends, family, and other reference groups do not significantly affect users' intention to use m-health services. It seems that the respondents, mainly young adults, show independence from the influences of people surrounding them to drive them to use HD. This is in line with the earlier research by Tam et al. (2020) on mobile applications in which service providers need to solve the problem of social pressure on users. Contrary to the findings in other countries such as Bangladesh and China (Alam et al., 2019; Alam et al., 2020b), where social influence significantly drives behavioral intention.

The fourth hypothesis explains the influence of facilitating conditions on behavioral intention. Facilitating conditions such as connected technology, instructions, content, and language used on HD have not shown a strong prediction of behavioral intention. This study's results align with the findings of Tam et al. (2020) that the ideal facilitating conditions do not significantly drive the intention to use the application every day. A good perception of the facilitating conditions is usually driven by the experience with the infrastructure offered by the service provider. Meanwhile, the HD users could be the first users of this app, so they would have no reference from previous experiences (Nysveen & Pedersen, 2016; Venkatesh et al., 2008). However, the study of Alam et al. (2020b) shows the opposite finding that facilitating condition drives the intention to use the application. The fifth hypothesis explains the effect of perceived reliability on behavioral intention. The result shows that perceived reliability is not supported as a factor that significantly affects behavioral intention for users of the HD application. A similar result is also shown by Alam et al. (2019), who demonstrated that perceived reliability has an insignificant impact on intention to use m-health services. This could happen since HD is relatively new from some users so that perceived reliability has not strongly formed on the mind and heart of new users. The findings of Bolt et al. (2022) indicate that a lack of knowledge about an application can reduce the engagement that discourages the usage of it.

The sixth hypothesis explains the effect of perceived risk on behavioral intention. The study's results stated that perceived risk did not significantly influence behavioral intention. The perceived risk in this context refers to the quality of the products (medicines) sold through HD and the security of their identity data. It seems that users in Indonesia are not concerned about the quality of the products offered and their data security. This finding differs from the result of some previous research findings that perceived risk has a negative influence on users' intention to use digital services that could be driven by different levels of awareness of the risk (Featherman and Pavlou, 2003; Klaver et al., 2021). However, those studies were conducted in the United States of America and the Netherlands, where the users are highly concerned about data security. Meanwhile, users in Indonesia still have low awareness of data security (Waranggani, 2022).

The seventh hypothesis explains that **price value has a significant effect on behavioral intention**. The price of HD application services is comparable to the value obtained for users. The results show similarities between users in Indonesia and China regarding their significant concerns about the costs incurred (Alam et al., 2019). Healthcare providers need to understand the purpose of users using m-health, which helps them to maintain their health without restrictions and to save on healthcare costs (Lee & Han, 2015). Based on Google's research in Indonesia, discounts and promos have fairly high search keywords. For Indonesians, discounts and promos can meet needs when the costs incurred are lower but provide more benefits (HIGOSpot, 2018). Therefore, the m-health provider in Indonesia should consider price value highly since it significantly encourages the adoption of the m-health application.

The last hypothesis tests the significant effect of behavioral intention on actual user behavior. Users generally try to use the HD application when they need further medical/professional services. This result confirms the findings of Alam et al. (2019) in Bangladesh and China and those in developed countries such as Canada and the United States whose behavioral intention positively influences actual usage behavior (Dwivedi et al., 2016).

5. Conclusion

This research shows that performance expectancy and price value significantly drive behavioral intention to use m-health applications. The findings indicated that performance expectancy (considered as benefit) and price (considered as cost) are the main considerations for consumers when they intend to use m-health. These two components create customer value (Sheth et al., 1991). Behavioral intention drives users to perform actual usage behavior toward m-health applications. As this study was carried out during the COVID-19 pandemic that created fears among customers, they simply consider customer value within the purchase behaviors. Therefore, m-health service providers must pay attention to the health service and value of the customers.

This research shows the UTAUT concept's essence in Indonesia's pandemic context. In that situation, the research shows the main factor considered by m-health users to adopt this technology is perceived value which is the comparison of perceived benefit and perceived cost. This finding has consequences to managerial implication that the m-health providers should focus their resources on the two factors. In developing performance expectancy, m-health service providers should know consumers' needs specifically to offer and fulfil the right solution. The benefits of access to the application should be the priority by providing user-friendly features that can be effectively and efficiently accessible at a convenient time and place.

On the other hand, providers should develop price value by set reasonable prices for the services and goods offered to consumers so that users experience the value in fulfilling their needs. The value exchange should benefit both the provider and consumer and be performed fairly to drive purchase intention and behavior. The findings of this study contribute managerially to explaining Indonesian consumer behavior. As price value has a significant effect on behavior intention, the company must pay attention to the value of the service so that the price offered shows appropriate benefits to increase their motivation to use m-health services. For instance, HD can offer free delivery charges for the users to save money and demonstrate greater loyalty in using the application in the future.

This research was conducted in a limited time and place, involving respondents in the greater Jakarta area during the pandemic. Thus, this context might not generally represent m-health service users in Indonesia. Further research can be carried out in several cities and involve other m-health platforms so that the findings can provide positive input for m-health using the same research model. This approach will help companies to apply win-win solutions for Indonesia's healthcare users. In addition, the behavioral intention of each user is influenced by the culture in each city (Dwivedi et al., 2016), so knowing the various perceptions of m-health applications can add a new perspective for companies to provide appropriate health services. Second, the UTAUT model can be further adapted to other smartphone applications such as internet banking (Sok & Chan, 2011), e-payment (Sivathanu, 2018), and mobile banking (Alalwan et al., 2017). Third, HD can use an internal database to research so that the findings will be more effective in building and improving the services its consumers expect.

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Author Contribution

Author 1: conceptualization, original draft, methodology, data collection, and analysis

Author 2: content review, supervision, and validation

Author 3: supervision, investigated, validated, visualization, and final editing

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Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships construed as a potential conflict of interest.

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