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MODELING FEMALE USERS' INTENTION TO USE HEALTH APPS IN INDONESIA: UTAUT2 WITH RISK AND ATTITUDE

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ABSTRACT: This study investigates determinants of intention to use mobile health applications, emphasizing the mediating role of attitude toward use. By drawing on UTAUT2 and TAM frameworks, it refines existing models through the lens of risk perception and gendered adoption behavior. Survey data from 187 Indonesian users—predominantly female (84%) and aged 31–40—reveal a distinct pattern: women exhibit stronger affinity for m-health platforms. Performance expectancy emerges as the most potent predictor of both attitude and intention, suggesting that perceived utility significantly shapes user receptivity. In contrast, effort expectancy, hedonic motivation, and price value bear negligible influence, while perceived risk exerts a modest dampening effect—chiefly linked to data security apprehensions. The study thus augments theoretical understanding of behavioral intention by threading attitude and risk into UTAUT2's fabric. For practitioners, the message is clear: cultivate usability, communicate tangible health benefits, and bolster privacy measures to accelerate adoption among key demographic segments.

Keywords: UTAUT2, Perceived Risk, Attitude Toward to Use, Intention to Use, Heathy Mobile Applications

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INTRODUCTION

Indonesia faces pressing health issues, both in physical and mental health domains. The aftermath of the COVID-19 pandemic has intensified mental health problems—such as stress, anxiety, and depression—among the population (BPS, 2023). Simultaneously, non-communicable diseases like diabetes, hypertension, and obesity remain prevalent due to unhealthy diets and sedentary urban lifestyles. According to Susenas data, 26 out of 100 Indonesians reported experiencing health complaints in 2023, a slight decrease from 29 in 2022 to 27 in 2021 (BPS, 2023).

Compounding this situation is the uneven distribution of healthcare professionals—only 20% of physicians work in rural areas (Mboi N et al., 2018), leaving many citizens with inadequate access to medical services. This inequity underscores the potential of mobile health (m-health) applications to deliver healthcare information and services across geographical divides (Sunjaya, 2019; Sunjaya AP et al., 2017; Sunjaya AP & Sunjaya AF, 2018). Applications like Halodoc, Alodokter, and SehatQ have grown in popularity, particularly after the COVID-19 outbreak (Temasek, 2024), but the adoption rate remains suboptimal (Harisandi & Wiyarno, 2023). While Indonesia ranks third globally in m-health adoption, with 57% of the population using health apps (Pusparisa, 2020), significant barriers such as low digital literacy, concerns about data privacy, and perceived risks hinder widespread utilization (Harisandi & Purwanto, 2023; Said, 2023).

The Unified Theory of Acceptance and Use of Technology (UTAUT2) offers a comprehensive lens for examining technology adoption by incorporating performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). However, research shows that external factors alone may not fully explain behavioral intentions in contexts where data sensitivity and risk perception are high.

In m-health, perceived risk—defined as users' subjective uncertainty about potential adverse outcomes such as data breaches or inaccurate medical advice plays a crucial role in adoption decisions (Bauer et al., 2009; Pavlou, 2003). Studies have confirmed that perceived risk can weaken users' attitudes and intentions to use digital health technologies (Liu & Yan, 2022; Saheb, 2020). However, this variable has often been overlooked in models focusing predominantly on benefit-driven predictors. Furthermore, the factor of habit, often considered an internal psychological construct, is commonly inserted into UTAUT2 as an external behavioral variable. This blending raises conceptual ambiguity, especially in healthcare settings, where routine use may be influenced more by internalized personal values than by systemic enablers.

To address these gaps, this study investigates the determinants of Indonesian users' intention to use mobile health applications by extending the UTAUT2 model with the perceived risk variable and analyzing attitude toward use as a mediator. The local context including technological infrastructure disparities and a gendered usage, provides a unique empirical foundation that distinguishes this study from others. The novelty of this research lies in three main contributions. This study offers a multifaceted contribution to the field of technology adoption by enhancing the UTAUT2 framework through the integration of perceived risk, thereby producing a more contextually relevant model for understanding m-health adoption in Indonesia. It also provides theoretical refinement by critically examining the conceptual placement of internal psychological constructs such as habit—within a model traditionally dominated by external behavioral drivers, addressing potential inconsistencies in prior frameworks. Additionally, the study's largely female-dominated sample reveals gender-related behavioral patterns in health app usage, offering empirical insights that may guide the development of gender-sensitive features and targeted segmentation strategies for mobile health applications and provides theoretical and practical insights into how digital health interventions can be better designed and communicated to diverse populations across Indonesia.

THEORETICAL REVIEW

The development of technology acceptance theory began with TAM (Technology Acceptance Model) developed by (Davis, 1989), which explains that a person's intention to use technology is influenced by two primary constructs, namely perceived usefulness (the belief that technology improves performance) and perceived ease of use (the belief that technology is easy to use). This model then developed into UTAUT (Unified Theory of Acceptance and Use of Technology) introduced by (Venkatesh et al., 2003) which integrates various previous theories, including TAM, by adding four primary constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as moderator factors such as age, gender, experience, and voluntary conditions. Furthermore, UTAUT was developed into UTAUT2 by (Venkatesh et al., 2012) for the context of individual users by adding three new constructs, namely hedonic motivation (pleasure in using technology), price value (perception of the value of benefits compared to costs), and habit (habit of using technology). This expansion makes UTAUT2 more relevant in explaining consumer technology adoption, especially in personal and routine technology use.

Within the UTAUT2 framework, several constructs collectively elucidate the nuanced dimensions of individual technology adoption. Performance expectancy—the belief that technology will enhance task performance—emerges as a key antecedent of behavioral intention (Venkatesh et al., 2012). When users anticipate functional gains, their propensity to adopt increases correspondingly. Equally vital is effort expectancy, or the perceived ease of technology use; simplicity and user-friendliness reduce cognitive resistance and foster acceptance (Venkatesh et al., 2012). Facilitating conditions, referring to the availability of supportive infrastructure and resources, further bolster adoption by removing external barriers to use (Venkatesh et al., 2012). Beyond utility, hedonic motivation—the intrinsic enjoyment derived from usage—plays a pivotal role, particularly for lifestyle-oriented technologies (Venkatesh et al., 2012). In tandem, price value, the user's evaluation of benefits relative to cost, becomes especially salient in consumer contexts where monetary or effort-related trade-offs are perceived (Venkatesh et al., 2012). Finally, habit, or the extent to which behavior becomes automatic through repetition, anchors sustained usage and transforms intention into practice (Venkatesh et al., 2012).

Based on previous research, performance expectancy (Venkatesh et al., 2003; Venkatesh & Bala, 2008) has a positive effect on user attitudes towards technology and intention to use it. Effort expectancy has also been shown to influence positive attitudes towards technology, where ease of use increases user attitudes (Baker & McNeill, 2023; Venkatesh et al., 2003) Hedonic expectancy, especially related to pleasurable experiences, shows a positive influence on user attitudes (Hsu et al., 2018; Thong et al., 2006). In addition, price value expectancy influences users' attitudes towards technology, where the fair price and value provided affect users' positive attitudes (Chen et al., 2019; Zeithaml & Berry, 1988). Facilitating expectancy also increases users' positive attitudes towards technology, especially when there is external support (Thong et al., 2006; Venkatesh et al., 2003). Finally, habit has been shown to positively influence users' attitudes toward technology use, as repeated behavior in interacting with a system reinforces users' familiarity and reduces cognitive effort. According to (Liman et al., 2022; Limayem et al., 2007a), habit is not merely an automatic behavior, but a reflexive psychological construct that emerges from repeated external experiences and environmental reinforcements. In the context of technology adoption, habit is formed through consistent use over time, where individuals internalize usage patterns based on prior interactions, feedback, and contextual triggers. Therefore, in this study, habit is treated as a learned behavioral disposition that plays a crucial role in sustaining user engagement with mobile health applications. These hypotheses are then proposed.

H1: Performance expectancy has a positive and significant effect on attitude towards use.
H2: Effort expectancy has a positive and significant effect on attitude towards use.
H3: Hedonic expectancy has a positive and significant effect on attitudes towards use.
H4: Price value expectancy has a positive and significant effect on attitudes towards use.
H5: Facilitating expectancy has a positive and significant effect on attitudes towards use.
H6: Habit has a positive and significant effect on attitudes towards use.

Perceived Risk

Perceived Risk refers to an individual's perception of the uncertainty and potential negative consequences that can arise from performing a behavior (Bauer et al., 2009) define Perceived Risk as subjective uncertainty about the negative consequences that may arise from an action. (Pavlou, 2003) states that Perceived Risk is an individual's subjective belief about the potential negative consequences of consumer decisions. Natarajan et al. (2017) in (Stefanny et al., 2022) suggests that Perceived Risk is the result of uncertainty that can cause harm to a product or service. Research by (Elanchelian, 2022;

Kleijnen et al., 2007) show that risk perception affects users' attitudes towards technology, with individuals who perceive low risk more likely to have a positive attitude towards technology use, especially in the context of digital service adoption.
H7: Perceived Risk has a positive and significant effect on attitude towards use.

Attitude Toward Use

Attitude Toward Use is a key variable in technology adoption research, which describes users' cognitive and emotional evaluations of technology. This attitude strongly influences an individual's intention to use the technology, which in turn affects usage behavior. In the Technology Acceptance Model (TAM) by (Davis, 1989), attitude towards use is influenced by two main factors, namely perceived ease of use and perceived usefulness. When individuals find the technology easy to use and provides significant benefits, their attitudes tend to be positive. In the Theory of Planned Behavior (TPB) by (Ajzen, 1991) attitudes towards technology are influenced by individual perceptions of the positive and negative consequences of the action, which can strengthen the intention to use the technology. Intention to Use, described in UTAUT2 by (Venkatesh et al., 2003) refers to an individual's desire or tendency to use technology, which in turn affects actual behavior in adopting technology. Research (Davis, 1989; Venkatesh et al., 2003) show that a positive attitude towards technology is directly related to the intention to use it.
H8: Attitude toward use has a positive and significant effect on intention to use.

This research shows that various factors such as performance expectancy, effort expectancy, hedonic expectancy, price value expectancy, facilitating conditions, habit, and perceived risk affect intention to use technology, either directly or through attitude toward use as a mediator. Performance expectancy plays an important role in shaping users' positive attitudes, which in turn influence the intention to use technology (Venkatesh et al., 2003; Venkatesh & Bala, 2008). Effort expectancy, although its effect is smaller, also affects user attitudes and intention to use (AlQudah, 2020; Venkatesh et al., 2003). Hedonic expectancy, which relates to the enjoyment of using technology, affects user attitudes and intention to use it (Hwang & Kim, 2007; Koufaris, 2002). Price value expectancy, especially in the context of digital services, affects users' attitudes towards technology and their intention to adopt it (Dickinger & Kleijnen, 2008; Suki, 2013) Facilitating conditions which include the availability of facilities and technical support also affect users' attitudes and their intention to use technology (Venkatesh et al., 2012; Zhang & Zhang, 2021) Habits affect users' attitudes and intentions in using technology, especially in familiar technologies (Limayem et al., 2007a). Perceived risk affects attitudes towards technology and intention to adopt it (Park & Kim, 2003). These hypotheses are presented, and the display of paths is in Figure 1.

H9: Performance expectancy has a positive and significant effect on intention to use which is mediated by attitude toward use.

H10: Effort expectancy has a positive and significant effect on intention to use which is mediated by attitude toward use.

H11: Hedonic expectancy has a positive and significant effect on intention to use which is mediated by attitude towards use.

H12: Price value expectancy has a positive and significant effect on intention to use which is mediated by attitude towards use.

H13: Facilitating conditions have a positive and significant effect on intention to use which is mediated by attitude towards use.

H14: Habit has a positive and significant effect on intention to use which is mediated by attitude towards use.

H15: Perceived risk has a positive and significant effect on intention to use which is mediated by attitude towards use.

RESEARCH METHOD

Sample and Collection Data

Using both offline and online survey methodologies, this study employed a quantitative strategy to gather data from Indonesian health app users in the major provinces of DKI Jakarta, Banten, Central Java, West Java, and East Java. Facebook, Instagram, and WhatsApp were among the media channels used in the online survey. Intention formation among Indonesian health app users was examined using a quantitative research approach, with particular attention paid to the UTAUT model, perceived risk, attitude toward usage, and intention to use. To ensure confidentiality, the authors did not use the complete names of the respondents or any other identifying information. A purposive approach was used to choose research participants, taking into consideration the elements listed in (1). gender. (2) Age. (3) Profession. (4) Level of education. (5) Duration of use of the health app. The study population consists of all Indonesian users of health apps. Given the vast number of users in Indonesia, a stratified random sampling technique will be employed to guarantee a representative sample. A representative sample was chosen from each stratum using stratified random sampling to guarantee that different industries and geographic regions were fairly represented. Random sampling was used in each stratum to lessen selection bias. The SEM-PLS 3.0 analysis tool will next be used to statistically examine the data outputs. Partial Least Square (PLS) is an additional Structural Equation Modeling (SEM) technique that can be used to explain whether two or more latent variables or independent variables and unmeasured dependent variables are related (Hair et al., 2014)

Measurement

Measurement There are nine variables in this study, namely: Performance expectancy, Effort expectancy, Hedonic expectancy, Price value expectancy, facilitating conditions, Habits, Attitude towards use and Intention to use. All questions are measured using several items on a five-point Likert scale scaled from strongly agree (5) to strongly disagree (1). We developed measurement items for each construct based on previous literature. To ensure content validity, we modified items from previous studies to suit the context of remote workers and digital technology. The number of indicator items used in this study is 20. With this number of items, the sample size of 187 meets the minimum sample criteria as described by (Hair et al., 2014).

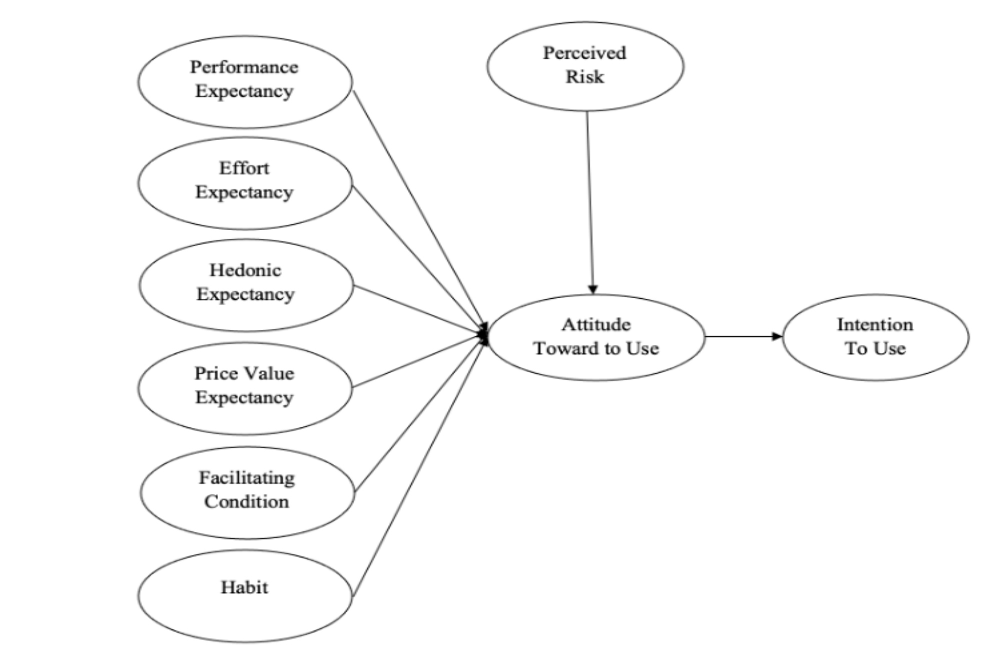

Figure 1. Conceptual Framework

Table1. Variable Operationalization

Variable	Indicators	Source
Performance Expectancy	3	(Venkatesh et al., 2003, 2012)
Effort Expectancy	3	(Venkatesh et al., 2003)
Hedonic Expectancy	2	(Venkatesh et al., 2016)
Price Value Expectancy	2	(Kim, 2015; Venkatesh et al., 2003)
Facilitating Conditions	2	(Venkatesh et al., 2003)
Habit	2	(Kang & James, 2007; Limayem et al., 2007b)
Perceived Risk	2	(Bauer et al., 2009; Lin et al., 2018)
Attitude Toward Use	2	(Ajzen, 1993; Venkatesh et al., 2003)
Intention to Use	2	(Ajzen, 1993; Venkatesh et al., 2003)

RESULT

Characteristics

Of the 200 surveys initially conducted, 187 surveys were completed in full, while 13 surveys were not completed collaboratively to collect data and were distributed via google form distributed using social media digital platforms. Table 1 displays the mean and standard deviation of the research questionnaire along with the respondents' answers. In this study, women constituted 84% of the respondents and 16% of the male respondents, this confirms that women are consistently found to be more proactive in accessing health information than men (Nikoloudakis et al., 2018). They often make decisions about treatment, symptom monitoring, and medical consultations for other family members. m-health applications greatly support this role (Bendsen et al., 2025; Moghaddasi, 2025) and 56% of them are between 31 and 40 years old.

Table 2. Demographic Characteristics

Demographic Characteristic	N	%
Gender		
- Male	30	0.16
- Female	157	0.84
Age		
- 20 – 30 years	50	0.27
- 31 – 40 years	105	0.56
- 41 – 50 years	21	0.11
- 51 – 60 years	7	0.04
- 61 years above	4	0.02
Job		
- Student	24	0.13
- Entrepreneur	41	0.22
- Government employees	30	0.16
- Private employees	56	0.3
- Freelancer	36	0.19
Education		
- Senior Hight School	56	0.3
Undergrad.	107	0.57
Master	21	0.11
Doctor	6	0.03
Experience		
- Under 1 years	26	0.14
- 1 – 2 years	28	0.15
- 3– 4 years	88	0.47
- 5 years above	45	0.24

Most indicators have a high outer loading value (see Table 3), the required outer loading value is 0.7 or more (Hair et al., 2014), so the results indicate that the indicators successfully measure the latent constructs represented.

Table 3. Research Questions

Variable	Operationalization	Indicator	Loading
Performance Expectancy (X1)	Individuals' perception that using technology will improve their performance (Venkatesh et al., 2012).	(Venkatesh et al., 2003, 2012) PE1: Benefits to improve performance	0.783
		PE2: Advantages in efficiency	0.876
		PE3: effectiveness, Increased productivity.	0.862
Effort Expectancy (X2)	The level of ease felt by individuals when using technology (Venkatesh et al., 2012).	(Venkatesh et al., 2003) EE1: Ease of use	0.689
		EE2: Simplicity in using the app	0.846
		EE3: Ease of learning the app	0.723
Hedonic Expectancy (X3)	The degree to which individuals perceive that others (such as friends, family, or coworkers) think they should use a particular technology (Venkatesh et al., 2012).	(Venkatesh et al., 2016) HE1: Emotional satisfaction	0.879
		HE2: Enjoyment in using the app	0.909
Price Value Expectancy (X4)	Price Value is a comparison between the perceived benefits of technology and the costs that must be incurred to use it (Venkatesh et al., 2012) .	(Kim, 2015; Venkatesh et al., 2003) PVE1: Fair price value	0.890
		PVE2: Price compatibility with benefits received	0.897
Facilitating Conditions (X5)	Facilitating Conditions is an individual's perception that infrastructure or technical support is available to help them use technology (Venkatesh et al., 2012).	(Venkatesh et al., 2003) FC1: Availability of required devices	0.902
		FC2: Available technical support	0.844
Habit (X6)	Habit is the degree to which individuals automatically use technology as part of their routine (Limayem et al., 2007b; Venkatesh et al., 2012).	(Kang & James, 2007; Limayem et al., 2007b) HA1: Habit of using the app regularly	0.907
		HA2: Integration of applications in daily life.	0.778
Perceived Risk (X7)	(Bauer et al., 2009) defines Perceived Risk as “subjective uncertainty regarding the possible negative consequences of an action.	(Bauer et al., 2009; Lin et al., 2018) PR1: Concerns about data security	0.703
		PR2: Uncertainty about the results or information the app provides	0.957
Attitude Toward Use (Z)	(Ajzen, 1991) individuals' attitudes toward an action, including the use of technology, are influenced by their perceptions of the positive and negative consequences of the action	(Ajzen, 1993; Venkatesh et al., 2003) AT1: Positive or negative attitude towards using the app	0.879
		AT2: Comfort and satisfaction in using the app	0.895
Intention to Use (Y)	(Teo, 2011) stated that Intention to Use is “the level of a person's desire to use a technology.	(Ajzen, 1993; Venkatesh et al., 2003) IU1: Future usage plan of the app	0.864
		IU2: Desire to adopt the app in the long term.	0.887

Source: SmartPLS output (2024)

In addition, Facilitating Conditions and Habit show that device availability, technical support, and usage habits are also important factors in application adoption. The results of the analysis also show that Perceived Risk is a concern for users, especially regarding data security and information uncertainty. However, Attitude Toward Use and Intention to Use show that overall, users have a positive attitude and strong intention to continue using health applications. This indicates that the benefits perceived by users are greater than the risks they perceive. These findings provide important implications for the development and marketing of health applications, namely by continuing to improve data security, providing accurate and reliable information, and facilitating the use of applications. Overall, this research model successfully explains the factors that influence user intention to use health applications. The results of this study can be a reference for health application developers to improve the quality of their applications and for marketers to design effective marketing strategies.

Table 4 shows descriptive statistics for the variables used in this study, including the mean and standard deviation for each variable. These variables describe aspects of user behavior that are predicted to influence the intention to use a technology or product. Overall, the mean values for most variables range from 3.5 to 3.9, indicating relatively positive attitudes and expectations toward technology use, although there is variation in individual perceptions of these factors. The relatively large standard deviations for some variables, such as Performance Expectancy and Perceived Risk, indicate that there is a diversity of opinions among respondents, which may be influenced by various contextual or individual factors.

Table 4. Descriptive Statisti*cs*

Variables	Mean	Standard Deviation
Performance Expectancy	3.8	1.6
Effort Expectancy	3.9	1.3
Hedonic Expectancy	3.9	1.3
Price Value Expectancy	3.4	1.4
Facilitating Conditions	3.6	1.4
Habit	3.5	1.4
Perceived Risk	3.5	1.6
Attitude Toward Use	3.5	1.5
Intention to Use	3.5	1.5

Source: SmartPLS output (2024)

Overall, in table 4 the Saturated Model shows a better fit compared to the Estimated Model, especially in SRMR, d_ULS, d_G, and Chi-Square. However, the difference between the two models is not too large, and both still show acceptable results in terms of model fit to the existing data.

Table 5. Descriptive Statistics

Criteria	Saturated Model	Estimated Model
SRMR	0.075	0.080
d_ULS	1.184	1.331
d_G	0.629	0.652
Chi_Square	894.321	913.762
NFI	0.545	0.535

Source: SmartPLS output (2024)

Validity and Reliability

Table 6 shows the validity and reliability results for the various constructs used in this study. The values presented include Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), which are used to assess the internal consistency and validity of the constructs. Overall, most of the constructs in this study showed Cronbach's Alpha, Composite Reliability, and AVE values that met the required standards, indicating that the constructs are reliable and valid for use in further research. However, some constructs, such as Effort Expectancy and Habit, had slightly lower Cronbach's Alpha values (i.e., below 0.70), which may indicate greater variation in respondents' responses to the constructs. Nevertheless, according to (Hair et al., 2014), Cronbach's Alpha values in the range of 0.60 to 0.70 are still considered acceptable in exploratory research or when the number of items per construct is relatively limited. Therefore, the internal consistency of these constructs remains adequate for analysis within the scope of this study.

Table 6. Validity and Reliability

Construct	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy	0.798	0.879	0.708
Effort Expectancy	0.621	0.798	0.571
Hedonic Expectancy	0.751	0.889	0.800
Price Value Expectancy	0.747	0.888	0.798
Facilitating Conditions	0.693	0.866	0.763
Habit	0.613	0.832	0.714
Perceived Risk	0.636	0.824	0.705
Attitude Toward Use	0.729	0.881	0.787
Intention to Use	0.697	0.686	0.767

Source: SmartPLS output (2024)

Table 7. above shows the results of the path analysis that illustrates the direct relationship between constructs in this research model. These results include the Original Sample value, Sample Mean, Standard Deviation, T-Statistic, and p-value for each relationship between variables.

Performance Expectancy (PE) -> Attitude Toward Use (AT) analysis results show that the Original Sample for this relationship is 0.297, with a T-Statistic of 3.824 and a p-value of 0.000. This shows that the relationship between Performance Expectancy and Attitude Toward Use is very significant, because the p-value is far below 0.05 (p-value = 0.000). This indicates that the higher the performance expectations for technology, the more positive the user's attitude towards its use is by 29.7%.

Furthermore, Attitude Toward Use -> Intention to Use analysis results show that the Original Sample for this relationship is 0.731, with a T-Statistic of 18.954 and a p-value of 0.000. This shows that the relationship between Attitude Toward Use and Intention to Use is very significant, because the p-value is far below 0.05 (p-value = 0.000). This indicates that the higher the attitude towards use, the higher the intention to use, by 73.1%. While other factors such as Effort Expectancy, Hedonic Expectancy, Price Value Expectancy, Facilitating Condition, Habit, Perceived risk do not show a significant effect on Attitude Toward Use, because the p-value is far above 0.05 (p-value = 0.000).

Table 7. Path Coeifficieint Value, t-Statistics, and P-Value (Direct Effect)

Path	Original Sample	*t*-value	p-value	Decision
Performance Expectancy -> Attitude Toward Use	0.297	3.824	0.000	Supported
Effort Expectancy -> Attitude Toward Use	0.080	0.949	0.343	Not Supported
Hedonic Expectancy -> Attitude Toward Use	-0.042	0.059	0.577	Not Supported
Price Value Expectancy -> Attitude Toward Use	-0.007	0.079	0.937	Not Supported
Facilitating Condition -> Attitude Toward Use	0.151	1.65	0.100	Not Supported
Habit-> Attitude Toward Use	0.043	0.482	0.630	Not Supported
Perceived Risk -> Attitude Toward Use	0.152	1.809	0.071	Not Supported
Attitude Toward Use -> Intention to Use	0.731	18.954	0.000	Supported
Performance Expectancy -> Attitude Toward Use -> Intention to Use	0.217	3.612	0.000	Supported
Effort Expectancy -> Attitude Toward Use -> Intention to Use	0.059	0.935	0.350	Not Supported
Hedonic Expectancy -> Attitude Toward Use -> Intention to Use	-0.031	0.554	0.580	Not Supported
Price Value Expectancy -> Attitude Toward Use -> Intention to Use	-0.005	0.079	0.937	Not Supported
Facilitating Condition -> Attitude Toward Use -> Intention to Use	0.111	1.663	0.097	Not Supported
Habit -> Attitude Toward Use -> Intention to Use	0.032	0.482	0.630	Not Supported
Perceived Risk -> Attitude Toward Use -> Intention to Use	0.111	1.818	0.070	Not Supported

Source: SmartPLS output (2024)

Table 8 shows the results of the analysis of the indirect effect between the constructs in this research model, especially through the mediating variable Attitude Toward Use (AT) on Intention to Use

(IU). Overall, the results of this indirect path analysis reveal that Performance Expectancy is the most significant factor in influencing user intention to use technology through Attitude Toward Use, for this path is 0.217, with a T-Statistic of 3.612 and a p-value of 0.000. This shows that this indirect path is significant with a p-value far below 0.05. This means that performance expectancy contributes to the intention to use technology through the formation of a positive attitude towards the use of technology. This result shows the importance of Performance Expectancy in driving user intention through changes in attitude towards technology. Meanwhile, other factors such as Effort Expectancy, Hedonic Expectancy, Price Value Expectancy, Facilitating Conditions, Habit, and Perceived Risk do not show a significant indirect effect based on a p-value greater than 0.05. although some of them are close to the significance limit.

DISCUSSION

This study reinforces Hypothesis 1, confirming that Performance Expectancy (PE) significantly influences Attitude Toward Use (AT). This aligns with Venkatesh et al. (2003) and Shin (2010), both of whom assert that users are more inclined to form positive attitudes when they perceive technology as enhancing performance. The strength of this relationship suggests that when users believe a health application contributes meaningfully to their personal well-being or efficiency, they are more likely to embrace it. For managers and developers, the implication is unequivocal: emphasize measurable functional outcomes in marketing and user onboarding—show, not tell, how the app improves lives.

In contrast, Hypothesis 2 is not supported; Effort Expectancy (EE) did not significantly influence AT. Although ease of use is often presumed essential, Venkatesh et al. (2003) clarify that its effect varies by context. In utilitarian settings like health tech, users may tolerate minor complexity if they perceive sufficient benefit. Managers would thus do well to focus less on minimalist interfaces and more on feature-rich utility, provided onboarding remains manageable.

Similarly, Hypothesis 3, proposing that Hedonic Expectancy (HE) influences AT, is rejected. Venkatesh et al. (2012) observed that enjoyment plays a lesser role in utilitarian systems, and this study confirms that users do not base their attitudes on pleasure when health outcomes are at stake. For product strategists, the implication is to prioritize functionality and reliability over gamification or aesthetic flair—users of health applications are not seeking amusement, but assurance.

The rejection of Hypothesis 4, which posited a significant influence of Price Value Expectancy (PVE) on AT, echoes findings in Venkatesh et al. (2012). Although price sensitivity is pivotal for intention, it appears insufficient to shape affective attitudes. Thus, health app providers should consider offering freemium models or clearly quantifiable benefits to justify cost at the decision stage—attitudes may not shift based on price, but intentions might.

Hypothesis 5 also fails to gain support, as Facilitating Conditions (FC) did not significantly influence AT. While FC has been shown to impact usage intentions (Venkatesh et al., 2003), its effect on attitude seems less pronounced unless infrastructure failure is blatant. Managers should ensure backend support is strong and visible, but need not expect that its mere presence will improve user perception unless failures are salient. Correspondingly, Hypothesis 6, Habit (HA) does not significantly influence AT. This confirms Venkatesh et al. (2012), who note that habitual behavior bypasses reflective attitude formation and instead feeds directly into intention or continued use. Managers seeking long-term engagement should focus on reinforcing repeat behaviors—such as daily notifications or health tracking streaks—to cultivate habitual usage, even if this does not immediately affect attitudes.

An intriguing partial finding concerns Hypothesis 7, where Perceived Risk (PR) exhibited a marginally significant positive relationship with AT ($p \approx 0.070$). This result diverges slightly from Pavlou (2003), who found risk generally suppressive. One possible interpretation is that users who recognize risk but still perceive control or trust may develop cautious but favorable attitudes. Herein lies a managerial goldmine: increase transparency and reinforce data protection messaging to convert risk-aware users into cautiously loyal adopters. As to the mediated effects, Hypothesis 8 is strongly supported: Attitude Toward Use significantly influences Intention to Use (IU), consistent with both Davis (1989) and Venkatesh et al. (2003). Attitude serves as a key psychological bridge; when nurtured properly, it reliably drives behavioral commitment. Practically, this underscores the value of shaping positive early impressions—via testimonials, user guidance, or expert endorsements.

However, Hypotheses 9–13, which test the indirect effects of EE, HE, PVE, FC, and HA on IU via AT, are rejected, with no significant mediation observed. These results affirm the limited role of attitude in translating these variables into intention. Managers should consider activating these constructs through direct pathways—e.g., incentive schemes for price-sensitive users or UX design for those sensitive to ease—rather than relying on attitudinal transformation. Finally, Hypothesis 14, concerning the indirect influence of PR on IU via AT, approaches significance ($p = 0.070$), indicating a subtle but noteworthy mediation effect. Though not conclusive, this suggests that perceived risk may influence intention by coloring user attitudes. For managers, this validates the investment in risk-mitigation communication—users may not flee from perceived threats if those risks are acknowledged and proactively managed.

The findings elevate Performance Expectancy and Attitude Toward Use as the most reliable levers for influencing health app adoption, while casting doubt on the conventional weight of ease, enjoyment, or price. For practitioners, the prescription is precise: design for functional value, message with clarity, reinforce trust, and enable habit—but do not expect attitude alone to carry the full load of persuasion unless performance speaks first.

CONCLUSION AND FURTHER STUDY

This study finds that Performance Expectancy (PE) is the most dominant factor influencing Attitude Toward Use (AT), which in turn significantly affects Intention to Use (IU) mobile health applications. This indicates that users are more inclined to adopt health technology when they perceive clear performance benefits such as efficiency, convenience, and effectiveness. In contrast, variables such as Effort Expectancy (EE), Hedonic Expectancy (HE), Price Value Expectancy (PVE), Facilitating Conditions (FC), Habit (HA), and Perceived Risk (PR) had insignificant direct or indirect effects, suggesting that these constructs may play more contextual or secondary roles depending on user segments or digital maturity. These findings reaffirm the applicability of UTAUT2 in the Indonesian setting while also signaling the need to reconsider and adapt behavioral models for local digital health engagement.

From a managerial perspective, the strong influence of performance expectations implies that developers and health service providers should emphasize functional outcomes and demonstrable benefits in their communication strategies. Providing users with evidence-based success stories, feature demonstrations, and trials could elevate trust and intention to adopt. Additionally, considering the high proportion of female users, gender-sensitive features and user interface designs may help increase satisfaction and adoption. For future research, scholars are encouraged to adopt mixed-method approaches to better understand the nuances behind insignificant factors, explore the roles of psychological moderators such as digital literacy and trust, and consider adapting or replacing less significant constructs to develop a more context-responsive model for health technology adoption in emerging economies.

ETHICAL DISCLOSURE

All participants provided written informed consent prior to participation. They were informed about the study's purpose, their voluntary participation, the right to withdraw at any time, and the confidentiality of their response

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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