Users' Intention to Use Mobile Health Applications for Personal Health Tracking

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Abstract

Currently, there are few studies related to the intention to use personal health tracking (PHT) application. This study aimed to analyze factors influencing the intention to use mobile health applications for PHT. The respondents were 516 individuals who had used a PHT application, such as Samsung Health, iOS Health, or MiFit. Data processing was done via using partial least squares–structural equation modeling (PLS-SEM). This study uncovered factors that can affect intention to use PHT applications, including perceived usefulness, social influence, facilitating conditions, hedonic motivation, habits, performance risk, and self-health awareness. It was found that perceived ease of use and self-reported health condition do not affect the intention to use PHT applications. This study can provide guidance on PHT application service providers for ensuring data accuracy, increasing user satisfaction when using the applications, and preventing privacy violation.

Keywords: personal health tracking, telemedicine, health technology, mobile health, Indonesia.

Introduction

The benefits that can arise from modern health technology have a great potential to reduce healthcare costs and prevent health problems that may arise. The Global Observatory for eHealth (GOe) defines m-health as a public health and medical practice supported by mobile devices (World Health Organization 2018). One of the benefits of m-health that can emerge from the presence of m-health in Indonesia is solving the problem of uneven health services. The use of m-health can evenly spread the distribution of health services in Indonesia, because

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problems caused by long distances and poor weather will no longer be salient (Nugraha 2017). At present, with the various potentials and benefits brought by m-health, there are also risks that can arise. One concern that often emerges is information security, especially security in the delivery of information and data storage (World Health Organization 2018). Unfortunately, the policy regarding e-health and m-health in Indonesia is still unclear. In addition, the development and use of e-health and health has not been evenly distributed throughout Indonesia (Nugraha 2017).

m-Health has entered Indonesia in various forms, one of which is applications that are embedded in various types of smartphones that are useful for recording at least one health indicator, such as weight, sports activities, or daily nutritional intake. Based on the World Health Organization (WHO), these applications are categorized as personal health tracking (PHT) (World Health Organization 2018). PHT is the use of cellular applications by clients using telephone-based sensors, health records, and other devices that can be worn by clients to monitor their health statuses.

At present, research on the intention to use smartphone-based PHT applications is not yet available. Further, research related to e-health in Indonesia is difficult to find (Nugraha 2017), and research on the application of m-health to PHT in this country is lacking. Given the number of smartphone users today, the factors that can influence the motivation or intentions of users to adopt the m-health applications for PHT need to be examined more deeply. Knowledge of these factors is expected to be used to serve Indonesian people by supporting their health. It is also hoped that understanding these factors can provide an overview for users and application developers, as well as the government and academics, regarding their strengths, weaknesses, roles, and the influence of PHT applications in Indonesia.

Based on the explanation given above, the present study seeks to address the following research question: What are the factors that influence one's intention to use PHT applications? This research can be useful for m-health application developers, especially in terms of PHT as an illustration of user behavior in Indonesia, and specifically, behavior that influences usage intentions. In addition, this research can provide useful knowledge to consider in developing health-related regulations and policies. In terms of its structure, the remainder of the paper is divided into three parts dedicated to the following topics: methods, results and discussion.

Literature Review

Rubin and Ophoff (2018) conducted research on the factors that influence the adaptation of the use of wearable technology by adapting the second generation Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The Rubin and Ophoff (2018) model has 7 variables that are considered as factors that can influence user intentions, namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Rubin and Ophoff (2018) found that only facilitating conditions and habits affect users' intentions to use wearable technology for health purposes. Li et al. (2019) has also conducted research on factors that can affect adaptation from the use of wearable technology, but specifically for parents over 60 years of age. Li et al. (2019) using the Smart Wearable Acceptance Model (SWAM). SWAM is a model adapted from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). SWAM includes facilitating conditions, compatibility, social influence, performance risk, perceived social risk, self-reported health conditions, perceived ease of use, and perceived usefulness. Li et al. (2019) found that facilitating conditions, compatibility, self-reported health conditions, and perceived usefulness are factors that can influence the intention to use wearable technology for people aged over 60 years. In addition to the two studies previously mentioned, many other studies have focused on wearable technology and its use as personal health tracking (Clawson et al. 2015). However, until now research on usage intentions in smartphone-based personal health tracking applications has not been available, and has focused more on wearable technology.

The design of the research model and factors in this study are based on several previous studies, namely, the research conducted in (Rubin and Ophoff 2018; Mangkunegara et al. 2018; Li et al. 2019). The factors that have been chosen are due to the results of previous studies and their suitability for the current research. Perceived ease of use and perceived usefulness are chosen because these two factors have often been considered for their influence on technological adaptation based on Technology Acceptance Model (TAM) (Davis 1985). Factors based on Unified Theory of Acceptance and Use Technology (UTAUT2) were chosen for the same reason. However, not all factors from UTAUT2 were included: The factors of performance and effort expectancy were not used because of their similarity with the perceived ease of use and perceived usefulness variables, which are indeed adaptations of these factors (Venkatesh et al. 2012). Other factors, such as price value, are also excluded because there are no costs incurred for the use of the application, which is the object of research. Health-related factors, such as those describing the state of health or user health concerns—referred to as self-health and self-health awareness—are used to enrich the views of this study based on previous research (Mangkunegara et al 2018; Li et al. 2019). From these considerations, a research model is formed, as illustrated in Figure 1.

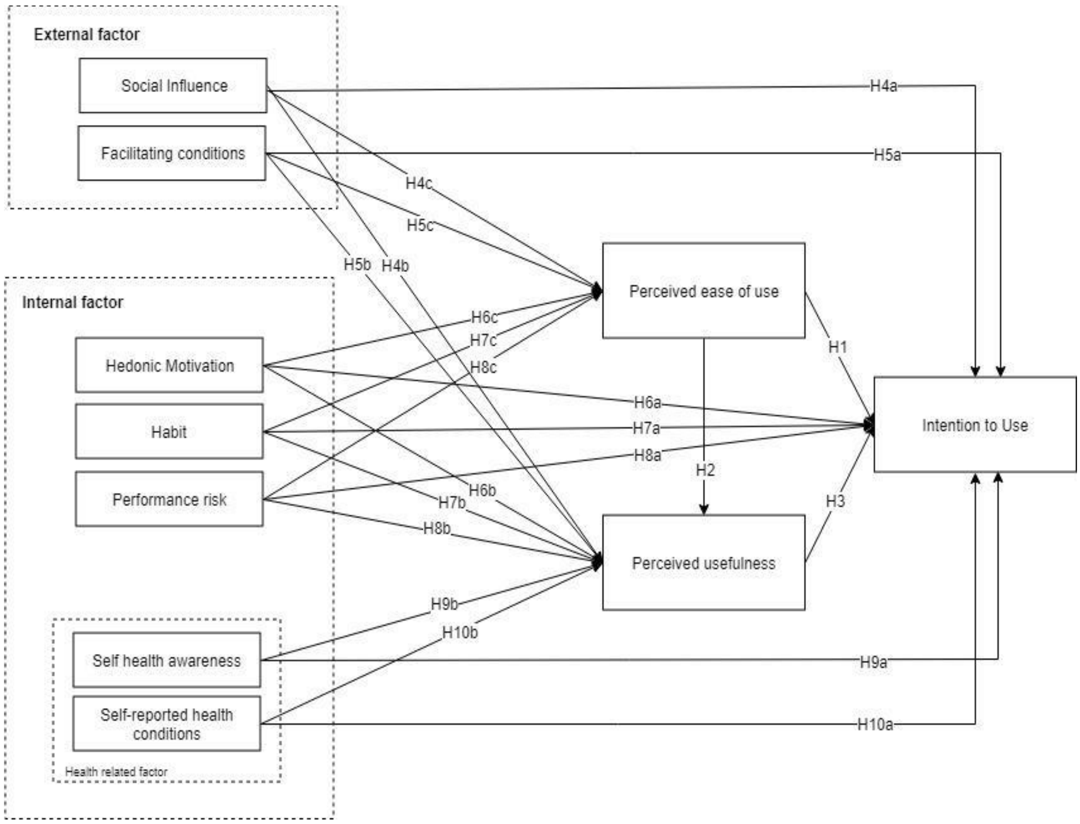

Figure 1. Proposed conceptual model

In TAM, it is said that an application that is easy to use can be easily accepted by the user. In addition, perceived ease of use influences how users perceive the usefulness of the application, because when applications are easy to use, their usability will be easier for the users to understand (Davis 1985). The relationship of perceived ease of use with intention to use and perceived usefulness has been proven in several previous studies regarding PHT (Rubin and Ophoff 2018) and m-health (Zhao et al. 2018).

H1: Perceived ease of use (PEOU) positively influences the intention to use (IU) for PHT applications.

H2: Perceived ease of use (PEOU) positively influences the perceived usefulness (PU) of PHT applications.

Perceived usefulness was defined by Davis (1985) and Chen et al. (2018) as an individual's level of trust in a technology's ability to improve the performance of his or her output. Li et al. (2019) defined perceived usefulness as a reflection of the benefits obtained by users when employing a technology. Several other studies have shown that perceived usefulness has an influence on users' intentions to adopt PHT applications and m-health (Li et al. 2017).

H3: Perceived usefulness (PU) positively influences the intention to use (IU) for PHT applications.

Social influence is defined as the level of trust an individual has toward the people around him or her who consider a technology important to use (Venkatesh et al. 2003; Li et al. 2017). The use of social influence factors is also known to affect the use of mobile applications on mobile devices. This is because the purpose of using mobile devices is connecting various people more easily, thereby strengthening social influence on their use (Yuan et al. 2015).

H4a: Social influence (SI) positively influences the intention to use (IU) for PHT applications.

H4b: Social influence (SI) positively influences the perceived usefulness (PU) of PHT applications.

H4c: Social influence (SI) positively influences perceived ease of use (PEOU) for PHT applications.

Facilitating condition factors have been used in several previous studies to examine the effect on the adaptation or use of health applications, as in research on wearable technology (Rubin and Ophoff 2018; Li et al. 2019) and health and fitness apps (Yuan et al. 2015). Users are more likely to be able to easily adapt to the use of a technology if they can easily access resources supporting its use (Rubin and Ophoff 2018). Good knowledge of the use of applications and the ease of accessing information related to an application can affect a person's level of trust that the application does not require a large amount of physical or mental effort to use.

H5a: Facilitating conditions (FC) positively influence the intention to use (IU) for PHT applications.

H5b: Facilitating conditions (FC) positively influence the perceived usefulness (PU) of PHT applications.

H5c: Facilitating conditions (FC) positively influence the perceived ease of use (PEOU) of PHT applications.

Currently, personal health monitoring applications, which are classified as health and fitness applications, have many entertaining features so that users will be more engaged (Yuan et al. 2015). Entertaining features represent one form of hedonic motivation, because they can provide pleasure. Hedonic motivation has also been proven to be one of the factors influencing technology acceptance and adaptation (Venkatesh et al. 2012; Yuan et al. 2015).

H6a: Hedonic motivation (HM) positively influences the intention to use (IU) for PHT applications.

H6b: Hedonic motivation (HM) positively influences the perceived usefulness (PU) of PHT applications.

H6c: Hedonic motivation (HM) positively influences perceived ease of use (PEOU) of PHT applications.

The use of mobile devices has become a habit in Indonesia, where smartphone use has reached 60% of adults in Indonesia (Hootsuite 2019). Indonesian people also people spend more time using more mobile devices than the average, where Indonesians spend 3.5 hours per day on mobile devices. This shows that the use of cellular devices is a habit in Indonesian society involving repeated behavior (Das et al. 2016). In Venkatesh et al. (2012), it was stated that repetitive behavior can be an ingrained intention, which will then be directed toward an individual's adaptation to use a technology (Rubin and Ophoff 2018).

H7a: Habit (HAB) positively influences the intention to use (IU) for PHT applications.

H7b: Habit (HAB) positively influences the perceived usefulness (PU) of PHT applications.

H7c: Habit (HAB) positively influences perceived ease of use (PEOU) of PHT applications.

Performance risk refers to the extent to which users perceive technology can bring unexpected risks, such as safety risk, functionality risk, and privacy violations (Li et al. 2019). The effect of risk from the use of technology was also applied in previous studies, such as Mangkunegara et al. (2018) and Zhao et al. (2018), which defined it as a factor that explains the risks arising when using m-health applications; these include performance, social, financial, and time risk. m-Health applications for PHT focus on recording users' daily activities. Recording these daily activities can pose risks, such as problems with data security.

H8a: Performance risk (PR) negatively affects intention to use (IU) for PHT applications.

H8b: Performance risk (PR) negatively affects the perceived usefulness (PU) of PHT applications.

H8c: Performance risk (PR) negatively affects perceived ease of use (PEOU) of PHT applications.

Loebnitz and Grunert (2018) defined self-health awareness as a factor that explains a person's awareness of his or her health condition and having confidence to manage it by adopting healthy behavior. Self-health awareness was used by Loebnitz and Grunert (2018) and Deng and Liu (2017) to represent factors that determine one's intentions to adopt healthy behaviors. According to Deng and Liu (2017), the more a person's beliefs about his or her health conditions and ability to manage his or her health increase, the more likely it is for the individual to adopt healthy behaviors, such as considering nutritional intake or seeking health-related information on mobile social media or health applications.

H9a: Self-health awareness (SHA) positively influences the intention to use (IU) for PHT applications.

H9b: Self-health awareness (SHA) positively influences the perceived usefulness (PU) of PHT applications.

In Li et al. (2019), the factor of the self-reported health condition (SRHC) was defined as a reflection of individuals' personal views about their status and health conditions at that time. Based on research in Li et al. (2019), it is known that SRHC significantly affects perceived usefulness and intention to use wearable technology for PHT. However, SRHC did not affect the respondents' perceived ease of use (Li et al., 2019). In addition, Zhang et al. (2017) showed that a good level of health can cause individuals to be more involved in carrying out health-related behaviors.

H10a: Self-reported health condition (SRHC) positively influences the intention to use (IU) for PHT applications.

H10b: Self-reported health condition (SRHC) positively influences the perceived usefulness (PU) of PHT applications.

Methodology

The approach used in this study was quantitative research involving an online questionnaire. The object of this study focused on PHT applications provided by smartphones, namely Samsung Health, iOS Health from the iPhone, and MiFit from Xiaomi. The research carried out in this study consisted of eight stages, namely, problem formulation, literature review, model formulation, instrument preparation, readability testing, data collection, data processing and analysis, and define conclusions and suggestions (Figure 2). Before the questionnaire was distributed, the authors first conducted an initial test by carrying out the readability test. Readability testing is done to determine whether the instrument can be understood by the respondent. The readability test in this study involved nine people who knew about one application between Samsung Health, iOS Health, or MiFit.

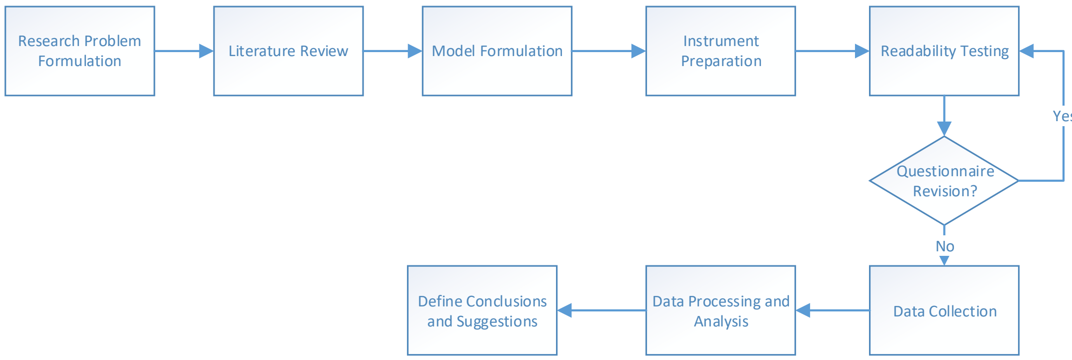

Figure 2. Research Methods

After passing the readability test, the questionnaires were published on various social media channels to reach more respondents. Appendix A described the measurement items used in this study. In addition to social media, we distributed the questionnaires through group chats. Data that had already been collected were processed using partial least squares–structural equation modeling (PLS-SEM) with SmartPLS 3.2.8 software. PLS-SEM was chosen because this research is an exploratory research.

Results

Respondents' Demographics

The questionnaire was distributed online and was available for nearly 2 months, from March 5 to April 22, 2019. The data that were obtained and validated were provided by 531 respondents. Of these, 516 respondents had used the Samsung Health, iOS Health, or MiFit application. The demographic summary of the respondents is given in Table 1.

Table 1. Respondents' Demographics

Demographics		Number of Respondents	Percentage (%)
Gender	Men	210	40.7
	Women	306	59.3
Age	< 20 years old	127	24.6
	20–30 years old	354	68.6
	31–40 years old	36	5
	41–50 years old	6	1.2
	> 50 years old	3	0.6
Education level	High school	221	42.8
	Diploma	35	6.8
	Bachelor's degree	241	46.7
	Master's degree	17	3.3
	Doctoral degree	2	0.4
Domicile	Greater Jakarta	275	53.3
	Outside Greater Jakarta on Java Island	177	34.3
	Beyond Java Island	64	12.4
m-Health application is used for PHT	Samsung Health from Samsung	222	43
	Health App from Apple	152	29.4
	MiFit from Xiaomi	183	25.4
Activities carried out on the m-health application (can choose more than one)	Sleep time analysis	291	56.4
	Walking distance	433	83.9
	Record of sports time	277	53.7
	Record nutrient intake	85	16.5
	Others	40	7.8

Data Analysis Using PLS-SEM

This stage of analysis involved the specification of the model, testing the outer model, testing the inner model, and finally, testing the model hypothesis. Convergent validity was tested for the value of the outer loadings and average variance extracted (AVE). The value of the outer loadings must be greater than 0.7, and the AVE value is recommended to be greater than 0.5 (Hair et al. 2011). Each indicator in this study fulfilled the requirements by having a value above 0.7. Next, the AVE value was checked, where the AVE value had to be more than 0.5. Details of the AVE value of each factor can be seen in Table 2.

Internal consistency testing can be done by checking the values of Cronbach's alpha (CA) and composite reliability (CR). In this study, these two criteria were considered in testing the reliability of internal consistency (Hair et al. 2016). This value is in the range of 0 to 1, with acceptable values above 0.7, while in exploratory research, values of 0.6–0.7 can still be accepted (Hair et al. 2016). Based on Table 2, it can be seen that all the CA and CR values were already above 0.7. Therefore, the two criteria in the reliability test of the outer model have been fulfilled. This indicates that the outer model has passed the reliability test.

Table 2. AVE, CA, and CR Values

Variable	**AVE**	**CA**	**CR**
FC	0.586	0.765	0.85
HM	0.789	0.865	0.918
HAB	0.776	0.855	0.912
IU	0.841	0.906	0.941
PEOU	0.824	0.893	0.934
PR	0.822	0.784	0.902
PU	0.727	0.875	0.914
SHA	0.633	0.806	0.873
SI	0.631	0.718	0.836
SRHC	0.63	0.711	0.836

Note: FC = Facilitating conditions; HM = Hedonic motivation; HAB = Habit; IU = Intention to use; PEOU = Perceived ease of use; PR = Performance risk; PU = perceived usefulness; SHA = Self-health awareness; SI = Social influence; SRHC = Self-reported health condition

This research is a one-tailed study and uses p-values for testing the hypotheses. For determining whether a hypothesis is accepted, it can be seen that the p-value received must be smaller than or equal to 0.05 or equivalent to a 95% significance level (Hair et al. 2011). The results and conclusions from the hypothesis can be seen in Table 3. Based on this, it can be concluded that there are 5 rejected hypotheses and 17 accepted hypotheses.

Table 3. Hypothesis Testing Results

Hypothesis		***Path coefficient***	***t*-Statistics**	***p*-Values**	**Result**
H1	PEOU -> IU	0.0698	1.5451	0.0613	Rejected
H2	PEOU -> PU	0.0983	2.1846	0.146	Accepted
H3	PU -> IU	0.2496	4.9814	0.000008	Accepted
H4a	SI -> IU	0.0645	1.9672	0.0247	Accepted
H4b	SI -> PU	0.1467	3.8964	0.0001	Accepted
H4c	SI -> PEOU	–0.0946	2.6658	0.0039	Accepted
H5a	FC -> IU	0.1219	3.1608	0.0008	Accepted
H5b	FC -> PU	0.0141	0.3576	0.3604	Rejected
H5c	FC -> PEOU	0.2937	7.3091	0.36×10^{-12}	Accepted
H6a	HM -> IU	0.1458	2.8376	0.0023	Accepted
H6b	HM -> PU	0.2032	4.6257	0.00002	Accepted
H6c	HM -> PEOU	0.3718	8.0647	0.65×10^{-13}	Accepted
H7a	HAB -> IU	0.258	5.6589	0.000001	Accepted
H7b	HAB -> PU	0.2674	6.3518	0.0000005	Accepted
H7c	HAB -> PEOU	0.1087	2.3744	0.0089	Accepted
H8a	PR -> IU	–0.1041	2.5624	0.0053	Accepted
H8b	PR -> PU	–0.1554	4.653	0.00006	Accepted
H8c	PR -> PEOU	–0.1518	3.79	0.0001	Accepted
H9a	SHA -> IU	0.0311	0.8345	0.2021	Rejected
H9b	SHA -> PU	0.2387	6.1567	0.00000003	Accepted
H10a	SRHC -> IU	–0.0295	0.7585	0.2242	Rejected
H10b	SRHC -> PU	–0.0395	0.9819	0.1632	Rejected

Discussion

When research is conducted on new users learning about technology, ease of use is important (Rubin and Ophoff 2018). Further, the use of mobile applications is affected by social influence. Based on data from the respondents who used a PHT application, approximately 50% of respondents learned about the application from social media, friends, or family. The relationship between social influence and intention to use, perceived usefulness, and perceived ease of use needs to be examined more deeply. This is because social influence can have different effects depending on an individual's social role in relation to other individuals. Next, users are also more likely to be able to easily adapt to the use of a technology if they can easily access resources that can support the use of this technology (Rubin and Ophoff 2018). However, external factors included in facilitating conditions are factors that do not affect an individual's view of the usefulness of the application because the surrounding environment can only influence intention and help use the application (Li et al. 2019).

Based on the data collected in this study, approximately 83% of respondents used one of these applications for recording distance (steps per day). Moreover, 56% used an application for analysis of sleep time and 53% for recording time engaged in sports. In the three applications, the feature for recording distance, exercise, and sleep time has targets that can be achieved. Achieving this target is one form of gamification that can lead to feelings of pleasure; in other words, it serves as a form of hedonic motivation (Yuan et al. 2015).

Based on questionnaire data, it is also known that the use of PHT applications has a high percentage of 47%. The repeated use of the PHT application illustrates that habit affects the user's intention to use PHT. This result was in line with Yuan et al. (2015) where usage for health and fitness applications is influenced by habitual usage. Rubin and Ophoff (2018) also finds the same thing that habit is a significantly positive influence on intention to use wearable technology. In addition, with people getting used to using smartphones, the use of PHT applications is seen as easy to use by the users.

The emergence of several risks also causes a negative influence on the views of the usefulness of the application. Based on the results of data from respondents, it is known that the problem that often arises in the use of this application is the data mismatches that sometimes occur. This is one example of a form of risk that has a negative influence on the perceived usefulness of m-health applications for PHT among users. A negative influence of performance risk on perceived usefulness was also found in this study. Further, there was a negative influence of performance risk on perceived usefulness. Therefore, it was concluded that performance risks, such as a data mismatch, slow application, and data security, had a negative influence on the perceived usefulness of the m-health applications for PHT. The same finding was also seen in Li et al. (2019).

The positive influence of self-health awareness on the intention to use was rejected in this study. The same finding was evident in research on the intention to use m-health applications in Indonesia (Mangkunegara et al. 2018). In this study, the hypothesis about self-health awareness and intention to use was not accepted. According to Mangkunegara et al. (2018), the use of the m-health applications in Indonesia is only based on external factors, such as seeking health information and other supporting features, but it does not relate to supporting healthy behavior. In addition, the use of the PHT application was also based largely on its availability on the user's smartphone. Therefore, it can be concluded that, indeed, there was no positive influence of self-health awareness on intention to use.

Further, the research conducted in Li et al. (2019) showed that health condition self-reporting significantly affected perceived usefulness and intention to use in terms of wearable technology for PHT. This result is contrary to the findings of this study, which revealed that self-reported health conditions do not affect perceived usefulness or intention to use concerning m-health applications for PHT. This is also contrary to the claim in Zhang et al. (2017) that a good level of health can cause individuals to be more involved in adopting behaviors to promote health.

Finally, this study has enriched the results of previous research related to the analysis of factors that influence the intention to use PHT applications in Indonesia. Differences in the results of this study can be found in the relationship of several factors, such as the absence of a relationship between perceived ease of use and intention to use. This discovery is different from the findings of Davis (1985), which reported that an application that is easy to use can be easily accepted by users. The practical implications of this study are that service providers must be able to provide services and complete help pages to support user trust as a facilitating condition. In addition, service provider can offer additional information related to health and fitness to enrich the user's knowledge in fields that are suitable for the application.

Conclusion

This study determined factors that can predict intention to use PHT applications, namely, perceived usefulness, social influence, facilitating conditions, hedonic motivation, habit, performance risk and self-reported health condition. From the results of the study, it was also found that approximately 65% of the respondents felt there was a data mismatch in the PHT application. This study has limitations where the respondents involved are more women and respondents located in greater Jakarta. Further research can consider the specific factors related to hedonic motivation and their causes in relation to the intention to use PHT applications, such as their relevance to gamification.

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