Analysis of Health Consumers' Behavior Using Self-Tracker for Activity, Sleep, and Diet

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Abstract

Background: *With the ever-increasing availability of health information technology (HIT) enabling health consumers to measure, store, and manage their health data (e.g., self-tracking devices), more people are logging and managing their own health data for the purpose of promoting general well-being. To develop and implement effective and efficient strategies for improving personal monitoring devices, a rigorous theoretical framework to explain the health consumer's attitude, intention, and behavior needs to be established. The aim of this study is to verify the HIT acceptance model (HITAM) in the context of the health consumer's attitude, behavioral intention, and behavior of utilizing self-trackers. Furthermore, the study aims to gain better understanding of self-tracking behavior in the context of logging daily activity level, sleep patterns, and dietary habits.* ***Subjects and Methods:*** *Forty-four female college students were selected as voluntary study participants. They used self-trackers for activity, sleep, and diet monitoring for 90 or more consecutive days. The logged data were analyzed and fitted to the HITAM to verify whether the model was suitable for capturing the various behavioral and intention-related characteristics observed.* ***Results:*** *The overall fitness indices for the HITAM using the field data yielded an acceptable fitness to the model, with all path coefficients being statistically significant. The model accounts for 66.8% of the variance in perceived usefulness, 43.9% of the variance in perceived ease of use, 83.1% of the variance in attitude, and 48.4% of the variance in behavioral intention. The compliance ranking of self-tracking behavior, in order of decreasing compliance, was activity, sleep, and diet. This ranking was consistent with that of ease of use of the personal monitoring device used in the study.* ***Conclusions:*** *The HITAM was verified for its ability to describe the health consumer's attitude, behavioral intention, and behavior. The analysis indicated that the ease of use of a particular HIT device stands as the most significant barrier in the way of increasing the efficacy of self-tracking.*

Key words: *self-tracker, quantified-self, health consumer, health informatics, medical records, telemedicine*

Introduction

In information technology (IT) developed nations, including the United States, the use of IT that tracks, analyzes, and provides feedback on various health and biometric data—diet, exercise, and activity level—is gaining popularity. For example, the "quantified self" (QS) movement, started in the United States, encourages people to use computers, smartphones, various electronic gadgets, and even pen and paper to track and manage one's sleep patterns, work, exercise, diet, and mood.[1] The philosophy behind the QS movement is that by using quantifiable data, which can be collected relatively easily through readily available technology, one can significantly improve the understanding of one's health and gain deeper insights into different approaches to improving health. This is a new phenomenon that arose out of 21st century innovations that made IT devices ubiquitous in our daily lives and hails as the beginning of new lifestyle habits. The followers of the QS movement understand that by incorporating various fun and easy-to-use IT devices and software into their lives, their quality of life can be improved. This phenomenon has not stopped at tracking and managing simple health-related metrics, such as weight or frequency of exercise, but has expanded into actively treating disease and health conditions. CureTogether, a Web site popular with the QS movement, provides forums for patients with similar symptoms and conditions, allowing them to freely share their information and empowers the users with increased control and decision-making powers.[2]

However, this type of consumer-empowering movement is still in its infancy. Because the technology to automate the process of health and biometric data tracking and analysis is not yet mature enough, there is a hard limitation placed on the process set by the individual consumer's efforts and level of dedication. For example, for the Diabetes Connect program, surprisingly high percentages of patients were unwilling to spend their efforts on self-tracking. There are likely several explanations to this behavior. First, managing a chronic disease can be complex and overwhelming for some patients, and they may be unwilling to take on more responsibilities. Second, many patients' minds hold the notion that a chronic condition is too complex for patients to manage on their own. Lastly, and most significantly, the technologies that enable self-tracking have not yet matured to the level suitable for addressing chronic disease management; they remain at the level only sufficient enough to attract an early adopter crowd, who can overcome technical challenges more easily.[3]

Until the technological advances that allow automatic health data collection without user intervention reach a critical maturity level, the accuracy and reliability of logged data depend largely on an

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individual consumer's attitude and behavioral intention. This is because health and biometric self-tracking is given an appropriate significance only when coupled with the consumer's efforts and desires to be informed. Therefore, a better understanding of the data collection process is a prerequisite for promoting healthy habits based on self-tracked data and obtaining meaningful feedback. To achieve this aim, we must investigate how consumers are using various health IT (HIT) devices that record activity, sleep, and diet, so that we can use this information to specify and develop guidelines for how future HIT devices ought to function and improve.

In this article, we investigate whether the HIT acceptance model (HITAM)[4] can capture the appropriate characteristics of self-tracking behavior. HITAM showed that perceived threat, perceived usefulness, and perceived ease of use significantly affected the health consumer's attitude and behavioral intention. Furthermore, the health consumer's health status, health belief and concerns, subjective norm, HIT characteristics, and HIT self-efficacy had a strong indirect impact on attitude and behavioral intention through the mediators of perceived threat, perceived usefulness, and perceived ease of use. Finally, an extended technology acceptance model in the HIT field was reported to be valid in describing the health consumer's behavioral intention.[4] By using the HITAM to describe various self-tracking behavior using HIT devices, more streamlined devices and technology with increased adoption rate and functionality will be developed.

RESEARCH QUESTIONS

- Does the HITAM explain the health consumer's self-tracking behavior? Specifically, what characteristics of health consumers and HIT devices ultimately affect the attitude, behavioral intention, and self-tracking behavior?
- How long can a consumer continuously track health data—activity, sleep, and diet?

OBJECTIVES

- Using actual user data, verify the hypothesis that the HITAM describes health consumers' self-tracking behavior, including but not limited to health consumers' attitude, behavioral intention, and behavior.
- Analyze the utility details of one of the most popular HIT device, the self-trackers.

Research Methods

One of the exogenous HITAM variables, "Health Status," was excluded because the research subjects were chosen from a pool of preconstrained demographics. On the other hand, the endogenous variable "Perceived Threat" was excluded because it is directly related to the "Health Status" variable. These variables are in gray type inside the dotted-line box in the upper left-hand corner in *Figure 1*.

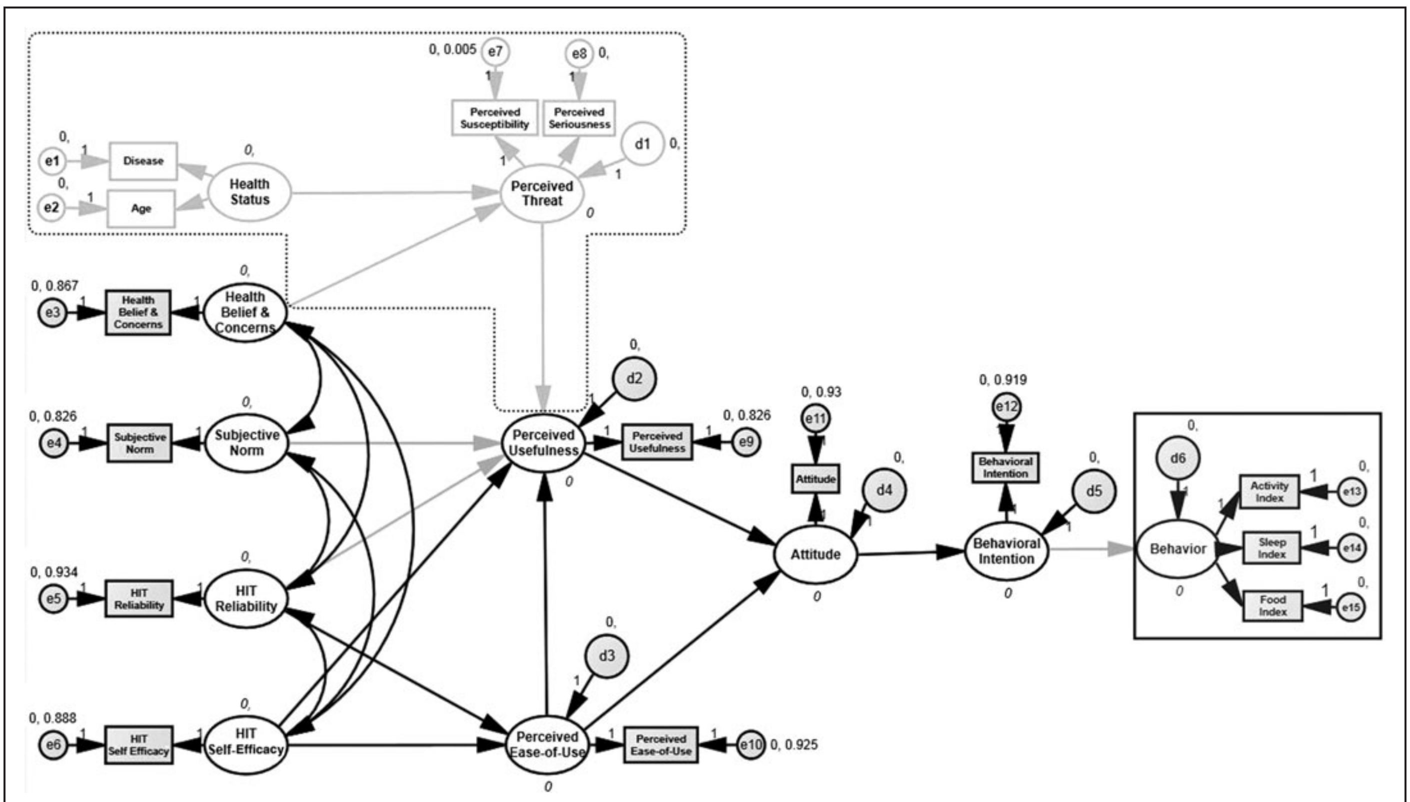

Fig. 1. Health information technology (HIT) acceptance model and the variables excluded or included in the study.

The endogenous variable "Behavior" was added to the model, as it is the primary focus of the study. Furthermore, three new measurement variables, "Activity Index," "Sleep Index," and "Food Index," were added to quantify the "Behavior" variable. These variables are in black type in *Figure 1*.

Based on the survey of various self-tracking devices currently used in South Korea, Fitbit™ (www.fitbit.com) was chosen; its ability to track activity, sleep, and diet fit the experimental design of this article closest.

Fifty-two female university students who were deemed proficient in operating the chosen personal monitoring device (PMD) were recruited. The pool was constrained intentionally to perform in-depth study of the specific demographics and their characteristics. Among the 52 students, 44 actively participated by using the PMD to track their activity, sleep, and diet habits.

Before their participation could begin, the participants were asked to attend one orientation and education session. They were given research participation consent forms, educated on the operation of the PMD devices, how to register on the product Web site, and miscellaneous supporting information. The University's Institutional Review Board preapproved the methods of the study prior to the orientation session.

The participants were asked to register and create an account on the product Web site and to wear the PMD for 3 consecutive months to track their various health-related data.

By simply wearing the PMD, users are able to track their activity levels throughout the day. To track sleep patterns, a switch on the PMD needs to be pressed once before the user falls asleep to enter into sleep-tracking mode and once again when the user wakes up to exit out of the mode. Dietary data are manually collected by the user logging on to the product Web site and entering the food, quantity, and time of each meal.

The data collected in the product Web site were retrieved as an Excel® (Microsoft®, Redmond, WA) spreadsheet and analyzed offline. *Table 1* contains the summary of the collected and analyzed data.

To verify the model, a questionnaire survey was used to collect data once at the beginning of the study. This questionnaire is identical to the one used to develop HITAM by Kim and Park,[4] with the exception of constraints on the age and disease categories being healthy females in their 20s.

The additional variable "Behavior" was analyzed via the PMD Web site data. To quantify the efforts of individuals to comply with the daily data logging behavior and evaluate the "Behavior" variable, the following metrics were defined:

For "Food Index":

1. the total number of days the user recorded her diet in the duration of the study (90 consecutive days)
2. the first any day of the study that was not logged followed by two more consecutive days that were not logged
3. the first any day of the study that was not logged followed by complete cessation of logs until the last day of the study

Table 1. Measured Variables from the Health Information Technology Acceptance Model and the Methods of Collecting Data

	VARIABLES	METHODS
Independent variables	Demographics (disease, age)	Questionnaire
	Health belief and concerns items	
	Subjective norm: 5 items	
	Perceived susceptibility: 3 items	
	Perceived seriousness: 4 items	
	HIT self-efficacy: 6 items	
	HIT reliability: 5 items	
Intervening variables	Perceived usefulness: 5 items	Questionnaire
	Perceived ease of use: 5 items	
	Attitude: 3 items	
	Behavioral intention: 3 items	
Dependent variables	Behavior = Activity Index + Sleep Index + Food Index	Web site data
	Activity Index: Out of 90 days, the total number of days where activity was logged; beginning from Day 1, the first day followed by 3 consecutive days of failing to log; and the first day followed by complete cessation of data logging	
	Sleep Index: Same as Activity Index	
	Food Index: Same as Activity Index	

HIT, health information technology.

"Activity Index" and "Sleep Index" have identical definitions as the "Food Index."

Results

INVESTIGATIVE ANALYSIS OF HIT DEVICE USE BEHAVIOR

The average age of the 52 participants who answered the preselection questionnaire was 24.56 ($\pm$4.9) years. Of these individuals, 44 agreed to wear the PMD and logged and tracked activity, sleep, and diet data. Although the maximum duration of data logging lasted for 124 days, only the data logged during the first 90 days were used in this study. This is because the experiment was designed to last 90 days only, and not enough participants participated beyond the agreed-upon experimental duration to provide statistically significant data. *Table 2* shows the summary of the statistics of the behaviors indices.

Among the three categories, the activity category had the largest continuous data tracking record (47.67 $\pm$ 31.52 days), followed by the sleep category (23.11 $\pm$ 23.448 days), with the diet being the category with the shortest continuous data tracking record (17.91 $\pm$ 21.197

Table 2. Descriptive Statistics of the Behavioral Indices

	NUMBER	MINIMUM	MAXIMUM	AVERAGE	SD
Activity					
Total number of days logged	44	0	90	44.89	27.754
First day followed by 3 consecutive unlogged days	44	0	90	36.57	29.278
First day followed by complete cessation of logging	44	0	90	54.43	29.408
Sleep					
Total number of days logged	44	0	86	22.73	22.304
First day followed by 3 consecutive unlogged days	44	0	90	17.09	20.045
First day followed by complete cessation of logging	44	0	90	40.23	30.250
Food					
Total number of days logged	44	0	68	17.57	19.625
First day followed by 3 consecutive unlogged days	44	0	67	14.39	19.222
First day followed by complete cessation of logging	44	0	83	25.50	24.843

SD, standard deviation.

days). The same trend was observed in the two other indices—"Activity Index" being the longest, followed by "Sleep Index" and then "Food Index."

THEORETICAL ANALYSIS OF HIT DEVICE USE BEHAVIOR: APPLICATION OF THE HITAM

The descriptive statistics of the variable scores and the reliability coefficients of the measuring tool in each category are shown in *Table 3*. It was found that each measured variable satisfied the assumption of the univariate normality. *Table 4* presents correlation coefficients for measured variables. The correlations among the measured variables ranged from 0.005 to 0.773.

Figure 2 presents the path diagram of the fitted model, and *Table 5* contains unstandardized and standardized estimates of the model. Originally, paths from "Health Status" to "Perceived Threat" and from "Perceived Threat" to "Perceived Usefulness" were proposed in the hypothetical model. However, these paths were removed because "Health Status" was removed on the account of the measured variables being controlled. This model exhibits a good fit to the data ($\chi^2=66.120$, $df=35$, $p=0.001$, $\chi^2/df=1.889$, root mean square error of approximation = 0.144). The model accounts for 66.8% of the variance in "Perceived Usefulness," 43.9% of the variance in "Perceived Ease of Use," 83.1% of the variance in "Attitude," and 48.4% of the variance in "Behavioral Intention" (*Table 5*). The statistically significant paths are shown in gray in *Figure 2*.

Discussion and Conclusions

The outcome of whether the research participants complied with the self-tracking behavior as defined in the study was consistent with our initial prediction. The activity category, because it did not require additional intervention from the user and was automatically collected, showed the highest level of compliance among the three categories. However, the users were not without some minor challenges, such as remembering to wear the device, taking care that the device is secure enough to prevent accidental loss, remembering to remove the device from the clothing before laundry, periodically charging the device, and bringing the device within the range of detection to the receiver connected to a computer at least once a week for data synchronization. Yet the device is small enough and with continuous advances being made to increase the ease of use to lower the entry barrier to use, the level of usability is increasing. Additionally, general curiosity toward a novel device, a sense of challenge to new tasks, and the ubiquitous availability of computing devices like computers and smartphones play a positive role in increased acceptance of the HIT device.

Because sleep tracking requires one additional step to facilitate, it showed a relatively lower compliance level compared with activity tracking. The act of toggling the device switch to enter into sleep tracking mode before falling asleep and once again upon waking served as a significant enough barrier to display a difference in compliance level relative to activity tracking. This result indicates the importance of automating the process of sleep tracking through innovative engineering for increased compliance by the users.

Finally, diet tracking remains as one of the biggest challenges in the self-tracking practice. Current technology cannot accurately track the amount and calorie of the user's food intake, even though the diet-related information is highly crucial in revealing the user's health behavior. There are some Web-based services that approximate the calories and amount of food eaten by user-submitted photographs of their meals. However, they require humans in the computation loop and are not fully automated processes.[5] In order to develop smart technologies (e.g., automatic approximation of a user's dietary habits through analyzing the sound of chewing), extensive research time and effort are required.[6] The ever-worsening challenge of managing obesity, including metabolic syndrome management, requires preliminary

Table 3. Descriptive Statistics of the Latent Variables and the Reliability Coefficients

	NUMBER	MINIMUM	MAXIMUM	AVERAGE	SD	KURTOSIS	SKEWNESS	CRONBACH'S ALPHA	NUMBER OF ITEMS
Health belief and concerns	44	17	34	26.70	4.009	−0.578 0.357	0.080 0.702	0.784	5
Subjective norm	44	17	35	25.09	4.045	0.434 0.357	−0.312 0.702	0.715	5
Perceived susceptibility	44	4	20	12.00	4.340	0.034 0.357	−1.007 0.702	0.774	3
Perceived seriousness	44	12	28	20.52	4.061	−0.012 0.357	−0.535 0.702	0.858	4
HIT self-efficacy	44	15	42	30.91	6.194	0.030 0.357	−0.121 0.702	0.873	6
HIT reliability	44	14	31	23.02	3.909	−0.018 0.357	−0.152 0.702	0.808	5
Perceived ease of use	44	17	35	27.84	4.822	−0.198 0.357	−0.662 0.702	0.860	5
Perceived usefulness	44	10	35	24.77	4.941	−0.229 0.357	0.558 0.702	0.825	5
Attitude	44	5	21	16.27	3.230	−0.925 0.357	1.992 0.702	0.898	3
Behavioral intention	44	10	21	16.50	2.610	−0.226 0.357	−0.160 0.702	0.811	3
Behavior	44	17	34	26.70	4.009	−0.578 0.357	0.080 0.702	0.945	9

HIT, health information technology; SD, standard deviation.

Table 4. Correlation Coefficients Among Measured Variables

	AGE	DISEASES	HEALTH BELIEF AND CONCERNS	SUBJECTIVE NORM	PERCEIVED SUSCEPTIBILITY	PERCEIVED SERIOUSNESS	HIT SELF-EFFICACY	HIT RELIABILITY	PERCEIVED EASE OF USE	PERCEIVED USEFULNESS	ATTITUDE	BEHAVIORAL INTENTION	BEHAVIOR
Age	1												
Diseases	−0.082	1											
Health belief and concerns	−0.092	0.099	1										
Subjective norm	−0.079	0.041	0.656^{b}	1									
Perceived susceptibility	0.163	−0.385^{b}	−0.096	0.066	1								
Perceived seriousness	−0.052	0.075	0.204	0.410^{b}	0.066	1							
HIT self-efficacy	0.246	0.197	0.335^{a}	0.405^{b}	−0.103	0.205	1						
HIT reliability	0.071	−0.130	0.211	0.295	0.073	0.165	0.408^{b}	1					
Perceived ease of use	−0.035	−0.015	0.363^{a}	0.404^{b}	−0.122	0.324^{a}	0.557^{b}	0.490^{b}	1				
Perceived usefulness	0.182	0.071	0.383^{a}	0.342^{a}	−0.133	0.364^{a}	0.665^{b}	0.424^{b}	0.712^{b}	1			
Attitude	0.080	0.153	0.405^{b}	0.379^{a}	−0.219	0.175	0.789^{b}	0.473^{b}	0.766^{b}	0.797^{b}	1		
Behavioral intention	0.133	0.000	0.559^{b}	0.645^{b}	0.029	0.497^{b}	0.565^{b}	0.313^{a}	0.631^{b}	0.545^{b}	0.590^{b}	1	
Behavior	1	−0.082	−0.092	−0.079	0.163	−0.052	0.246	0.071	−0.035	0.182	0.080	0.133	1

$^{a}p>0.1$, $^{b}p>0.05$.

HIT, health information technology.

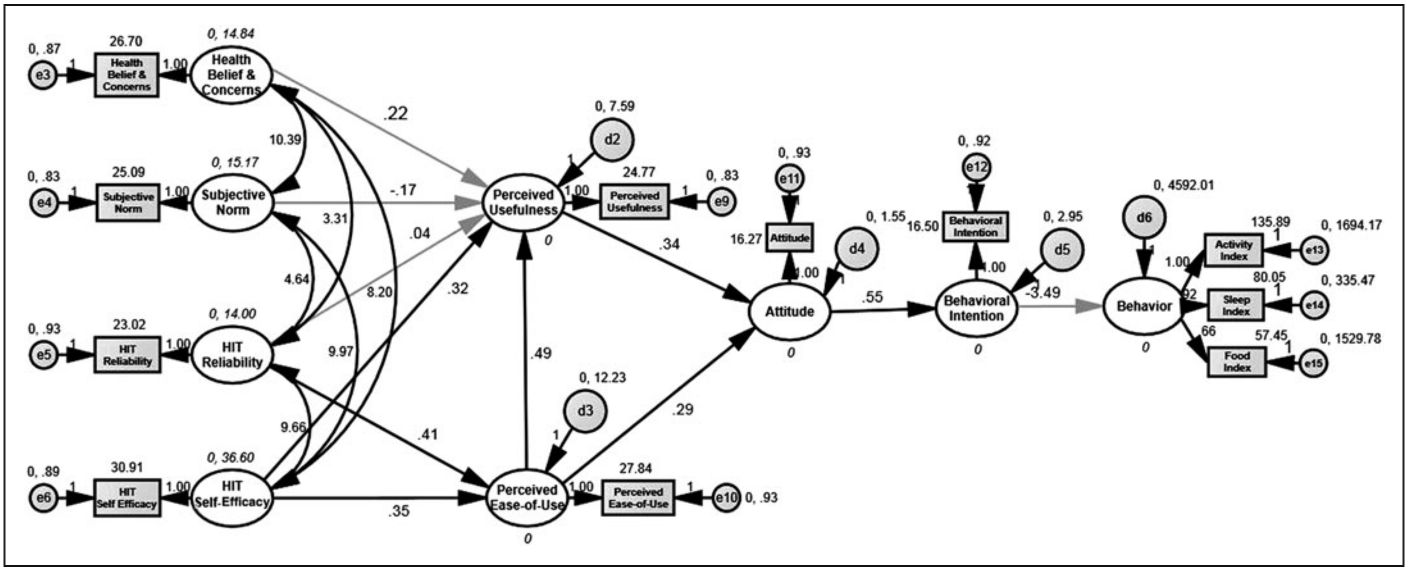

Fig. 2. Path diagram of the health information (HIT) technology acceptance model.

data obtained from meal tracking. Therefore, it is imperative to address the ways in which meal tracking can be better streamlined and automated. The benefits of the QS movement (digitization and management of various aspects of one's health and biometric data) must be subjected to various research efforts and further encouraged in the future.

In this study, a modified HITAM that constrained the age and disease variables was used to determine whether the remaining variables have significant effects on health consumers' health behavior. The analysis revealed that the HITAM was consistent in its prediction, with two notable exceptions: (1) "HIT Reliability," "Health Belief and Concerns," and "Subjective Norm" have a weak effect on "Perceived Usefulness," and (2) "Behavioral Intention" has a weak effect on "User Behavior."

The HIT device's inherent characteristics to produce behavioral intention are not sufficient to bring about meaningful changes in the user behavior. The current trend in the field is to emphasize the need to consider the emotional factors experienced by the study participants toward specific behaviors. This is consistent with our observation that behavioral intention and attitude are crucial in using HIT devices to

Table 5. Evaluation of the Health Information Technology Acceptance Model

ENDOGENOUS AND EXOGENOUS VARIABLES	REGRESSION WEIGHTS	SE	STANDARDIZED REGRESSION WEIGHTS	CR (*T* VALUE)	*P*	SMC
Perceived_EaseOfUse ← HIT_Reliability	0.410	0.172	0.329	2.385	0.017	0.439
Perceived_EaseOfUse ← HIT_SelfEfficacy	0.348	0.104	0.452	3.342	[a]	
Perceived_Usefulness ← HIT_Reliability	0.044	0.153	0.035	0.288	0.773	0.668
Perceived_Usefulness ← Subjective_Norm	−0.171	0.182	−0.139	−0.940	0.347	
Perceived_Usefulness ← HIT_SelfEfficacy	0.319	0.102	0.404	3.130	0.002	
Perceived_Usefulness ← Perceived_EaseOfUse	0.489	0.135	0.477	3.611	[a]	
Perceived_Usefulness ← Health_Belief_Concerns	0.217	0.176	0.175	1.236	0.216	
Attitude ← Perceived_Usefulness	0.341	0.080	0.538	4.243	[a]	0.831
Attitude ← Perceived_EaseOfUse	0.285	0.082	0.440	3.459	[a]	
Behavioral_Intention ← Attitude	0.550	0.106	0.696	5.172	[a]	0.484
Behavior ← Behavioral_Intention	−3.488	4.781	−0.122	−0.730	0.466	0.015

CR, critical ratio; HIT, health information technology; SE, standard error; SMC, squared multiple correlation.

[a] $p = 0.00$.

manage health. Ultimately, this suggests that even if a user admits to the rational and justifiable reasons for changing one's behavior through proper logical derivation, such justification alone is still not sufficient to change the user's behavior. Additionally, it is difficult to anticipate actual changes in behavior based solely on behavioral intention.

Lastly, even with the straightforward rationale that presenting someone with the benefits of behavior changes will have a positive outcome on the person's actions, the study showed insufficient compliance level. This observation may be due to the specific demographic addressed here—healthy young females—and their inherent characteristics. The young and healthy participants do not yet comprehend the health benefits of being mindful of one's health, whereas in an older population group, increased awareness toward the consequences of one's health habits is expected. This suggests that different factors must become the focal points of model analysis when addressing different age groups, and further verification of the model across various age groups, gender, and sociocultural backgrounds is required. Additionally, a more detailed model that can explain the relationship between behavior and behavioral intention needs to be developed. This type of continued and varied efforts to verify various hypotheses in the field will have lasting impact on the application and evaluation of health-related HIT, expand the knowledge base critical to device development, and serve as the foundation for providing quality healthcare developed on solid scientific research.

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Disclosure Statement

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