Determinants of Adoption of Smartphone Health Apps among College Students

Jaehee Cho, PhD; Margaret M. Quinlan, PhD; Dongjin Park, PhD; Ghee-Young Noh, PhD

***Objective*: To examine the effects of cognitive and contingent factors on the adoption of smartphone health apps, focusing on the technology acceptance model (TAM). *Methods*: American college students (N = 422), who currently owned smartphones but were not using health apps, completed an online survey. *Results*: Results from a path analysis mostly supported the proposed hypotheses, showing that subjective norm, health consciousness, health information orientation, and Internet health information use efficacy significantly affected the main components of TAM. *Conclusion*: Study findings provide scholars and practitioners with an empirical model of explaining the cognitive and micro-mechanisms of determining the adoption of health apps, especially among younger populations.**

***Key words*: smartphone health apps, technology acceptance model (TAM), health consciousness, health information orientation, Internet health information use efficacy**

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Mobile phone penetration rates are climbing across the world as mobile phone ownership becomes becoming increasingly common. According to Rainie, 91% of Americans older than 18 years old own a mobile phone, making it by far the most popular technological device owned by adults.[1] In addition, roughly 56% of American adults now own smartphones.[1] Consumers' increasing use of mobile technology in the US has dovetailed with an increasing interest in preventive healthcare measures and self-monitoring of one's health due to the increased prevalence of chronic diseases such as obesity, diabetes, cancer, and cardiovascular disease.[2]

The concept of mHealth has emerged as a key beneficiary of the dual emphasis on technology and an increasing interest in healthy behavior and data monitoring.[3,4] Indeed, heath apps designed for smartphones, a key component of mHealth, have increased notably and become more popular.[5,6] In March 2013, there were approximately 97,000 health apps available for mobile phones.[7] The utilization of health apps are popular among the following demographic groups: younger individuals, females, and those with higher levels of education.[5] The age group of 18 to 29 years more actively used health apps.[5] The 2 main purposes for using health apps are exercise and diet,[5] and there has been an increase of apps for specific medical purposes, such as Type II diabetes, high blood pressure, and other medical conditions.[8-13]

Whereas previous research has focused on myriad aspects related to health apps, such as general trends, educational purposes of health apps use, and effectiveness of specific functions of health apps,[5,8-15] there is a research lacuna regarding the micro and fundamental mechanisms that determine individuals' adoption of health apps. Research by Lim et al[6] on Singaporean women's adoption of smartphone apps for health information by applying the technology acceptance model (TAM) was a path-breaking study assessing why individuals adopted certain apps. However, the main limitation of the Lim et al study was that it did not incorporate the potential predictors of 2 main components of TAM—perceived usefulness (PU) and perceived ease of use (PEOU). That is, the Lim et al study did not fully consider the potential factors that determine PU and PEOU.

Therefore, to assess reasons for adopting health apps on smart devices, the current study incorporated multiple factors that influence PU and PEOU in regards to adoption of health apps. Based on TAM II, we considered health consciousness, health information orientation, eHealth literacy, Internet

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health information use efficacy, and subjective norm as the main factors of consideration.

Theoretical Framework

TAM theoretically relies on the main propositions of the Theory of Reasoned Action (TRA).[16] TRA discusses how an individual's intention to engage in a certain behavior is determined by cognitive factors. Thus, TAM places considerable attention on the factors that determine a person's adoption of a specific technology.[17,18] Indeed, due to the model's strong predictive power, TAM has been widely applied in research on various technologies.[18] There has also been increasing research on the adoption of health technologies and services.[19,20] Thus, our study used TAM as its main research tool for scrutinizing the adoption of health apps on smart devices.

The original TAM argues that 2 primary factors determine people's behavioral intentions to adopt and use a given technology: "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU).[17] PU is defined as the extent to which a person believes that the use of technology will help improve his/her performance.[16] Venkatesh and Davis[18] defined PEOU as the degree to which a person believes that he/she will be able to use a given technology in a convenient manner without much effort.

Although the original TAM has been well known for its rigor in testing user acceptance of new technologies, scholars have emphasized the necessity to extend the original TAM, incorporating factors that explain those main components.[21,22] Indeed, there has been substantial success in expanding TAM, proposing diverse versions of TAMs (eg, TAM II, UTAUT) in different contexts.[23,24]

In particular, TAM II, unlike TAM I, includes social influence— particularly the subjective norm— as an additional important antecedent of PU.[18] Here, subjective norm can be defined as a "person's perception that most people who are important to him/her think he/she should or should not perform the behavior in question."[18(p. 187)] As the extension of TAM, scholars have intensively studied social influence.[18,25,26] Thus, considering the advanced prediction power of TAM II, this present study relied on TAM II.

Predictors and Outcomes of PU and PEOU

Following the main theoretical thrust of TAM II on social influence, this research incorporates additional constructs, specifically the following predictors of PU and PEOU of health apps: health consciousness, health information orientation, eHealth literacy, Internet health information use efficacy, and the subjective norm. Health consciousness is conceptualized as the extent to which individuals have interests in and are aware of their own health conditions and well-being.[27-28] More health-conscious individuals are likely to seek health information through diverse external channels to manage their own health effectively.[27,29] Thus, considering health apps' main role of providing health information, it is reasonable to argue that health conscious people will perceive health apps as useful tools for managing their health. These lead to the following hypotheses.

H1: Health consciousness will positively predict the perceived usefulness of health apps.

Next, based on the conceptualization of health orientation,[28] health information orientation is a specific form of health orientation:[30] the concept measures the extent to which a person actively seeks health information through diverse sources. Health information orientation is inherently relevant to health information-seeking behaviors through various channels.[27] Based on this claim, the following hypothesis was developed and tested.

H2: Health information orientation will positively predict the perceived usefulness of health apps.

In addition to cognitions of health consciousness and health information orientation, it is often more important for individuals to comprehend health information.[31,32] Unless a person adequately understands received health information, s/he is more likely to devalue the information, perceiving less usefulness of the information source. In regards to comprehension of online health information, eHealth literacy could be defined as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem."[31(p. 2)] Here, it is possible that a person can understand health information online better because s/he can decipher the given information. This ability to decipher online health information could be related to the perceived ease of using health apps. Consequently, this study established the following hypothesis.

H3: eHealth literacy will positively predict the perceived ease of using health apps.

Yun and Park[33] examined the role of Internet health information use efficacy for determining perceived ease of use of the Internet to seek disease-related information. To develop this concept in further detail, these authors connected self-efficacy with Internet health information. Self-efficacy is individuals' self-cognitive ability to achieve purposed goals. Thus, Internet health information use efficacy can be conceptualized as individuals' cognitive ability to seek health information through the Internet. In their study, Yun and Park[33] found a strong direct effect of Internet health information use efficacy on perceived ease of use. However, there was no significant effect of Internet health information use efficacy on perceived usefulness. Therefore, considering these findings, this study tested the following hypothesis:

H4: Internet health information use efficacy will positively predict the perceived ease of using health apps.

Previous studies have shown the significant role of social influence in determining a person's technology adoption.[25,26] More specifically,

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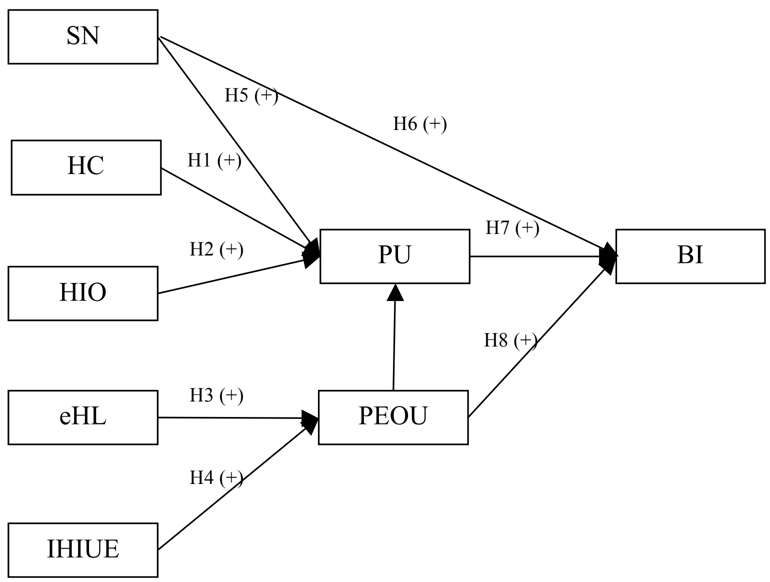
Figure 1
Theoretical Model for Study



Note.
SN = Subjective Norm, HC = Health Consciousness, HIO = Health Information Orientation, eHL = eHealth Literacy, IHIUE = Internet Health Information Use Efficacy, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, BI = Behavioral Intention to Use

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according to Fulk, Schmitz, and Steinfield,[34] 2 theories—the social learning theory and the social information processing theory—explained the significance of social norms for adopting new technologies. Whereas social learning theory posits that an individual constructs social meaning by observing other behaviors, social information processing theory explains influential others' influence on an individual's attitudes and behaviors. This implies that individuals' final decision to adopt new technologies is significantly dependent on information from influential others that may influence their decision. TAM II proposes direct effects of a subjective norm on perceived usefulness and intention to use.[18] That is, influential others' (eg, family members, friends) opinion and evaluation of a new technology plays a key role of determining one's adoption of the technology. Based on these propositions, we established the following hypotheses:

H5: Subjective norm will positively predict the perceived usefulness of health apps.

H6: Subjective norm will positively predict the intention to use health apps.

Lastly, previous studies of TAM and extended TAMs have provided ample evidence of supporting direct and indirect effects of PU and PEOU on behavioral intention to use (BI) a given technology.[33,35] Building on the previous findings, this study tested direct effects of PU and PEOU on BI through H7 and H8. In addition to direct effects, previous studies have often analyzed PU's mediating effect of the relationship between PEOU and BI.[33] Thus, this study tested the last hypothesis (H9).

H7: Perceived usefulness of health apps will positively predict the intention to use them.

H8: Perceived ease of use health apps will positively predict the intention to use them.

H9: Perceived usefulness of health apps will positively mediate the effect of perceived ease of use health apps on the intention to use health apps.

METHODS

Participants and Procedure

To test the posited hypotheses, we collected quantitative data through the online survey tool SurveyMonkey. Data collection occurred between March 19 and March 28 after study approval was granted by the Internal Review Board (IRB) of the University of North Carolina at Charlotte. Date were collected from a convenience sample. The study's 2 primary investigators contacted 6 professors with whom they had close personal relationships in the United States; the 7 universities ultimately contacted were located in the northern, southern, middle, and eastern regions of the United States. An invitation email was sent to the 6 professors who, in turn, distributed the email to students currently

Figure 2
Screenshots of Health Apps

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enrolled in their classes. The invitation email included the IRB-approved informed consent form, as well as the link to the online survey. Students who participated in the online survey received extra credit. After the initial invitation email, 2 reminder emails were sent out during the 10 subsequent days of data collection. The inclusion criterion of the study was ownership of a smartphone. Only students who agreed to the consent statement of survey participation were allowed to access and complete the survey. In total, we collected surveys from 422 participants who were smartphones users, but not users of health apps. The majority of the students were female (59.7%); the average age of study participants was 22.1 years. The participants were evenly distributed in terms of school year: freshman (24.2%), sophomore (22%), junior (27.5%), and senior (26.3%).

Considering survey participants had little information or exposure to health apps, we provided them with multiple screenshots of the instructions for using 2 different apps. Although there is a wide diversity of health apps available for consumers, this study focused on 2 particular health apps, "*Runkeeper*" and *"Lose It*," rather than providing information on a greater number of apps; this decision was made to reduce the amount of information given to study participants that could possibly hinder their understanding. "*Runkeeper*" and "*Lose It*" were selected for 2 reasons. First, according to Fox and Duggan,[5] the 2 biggest motivations to use health apps were: (1) to become fit through exercise and; (2) to lose weight. Indeed, the authors found that 38% of health app users used such apps for exercise and fitness, whereas 43% of them did so for diet or weight loss. Individuals' use of health apps for medical purposes was relatively low: 5% for blood pressure check, and 2% for medication management (eg, alerts). Second, the selected health apps were 2 of the most popular health apps (appcrawlr.com). To help study participants understand how to use the health apps, we made screenshots of how to set up the app on one's smartphone and start to use the health apps. For example, in regard to 'Lose It,' we made 12 screenshots of the steps of setting up and calculating calories for a given goal (Figure 1). Participants were then asked to read the instructions. After reading all of the screenshots instructing the use of health apps, survey participants completed the remaining survey questions mainly about perceptions of health apps.

Instruments

All scales were measured using a 5-point Likert-type scale (eg, *1 = Strongly disagree*, *5 = Strongly agree*). All reliability tests presented acceptable Cronbach's alpha scores (higher than .70) for all of these scales. The internal consistency reliability was chosen to check how consistently the research participants responded to the multiple items measuring each variable. Particularly when composite measurements are used, the internal consistency reliability is checked to test for the consistency with which the multiple items are measuring the same construct.

Health consciousness. To operationalize this variable, we used Dutta-Bergman's scale of health-consciousness attitude, which is originally composed of 5 items.[28] Because of low standardized regression weights from confirmatory factor analysis (CFA), 2 items were removed from further analysis. Examples of used items were: (1) I do everything I can in order to stay healthy; and (2) It is very important that I am in the healthiest condition possible. The reliability for this measurement (M = 3.56,

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SD = .78, N = 422) was acceptable (α = .77).

Health information orientation. Dutta-Bergman's scale of health information orientation was used to operationalize this variable.[28] Six items were used to measure this variable. Examples of the items used in the scale were: (1) The amount of health information available today makes it easier for me to take care of my health and; (2) When I take medicine, I try to get as much information as possible about its benefits and side effects. The reliability test showed an acceptable Cronbach's alpha (M = 3.77, SD = .67, N = 422, α = .86).

eHealth literacy. Six items from Norman and Skinner's scale were used to operationalize eHealth literacy.[31] Examples of these items were: (1) I know how to use the Internet to answer my questions about health; and (2) I know how to use the health information I find on the Internet to help me. The reliability score for this measurement (M = 3.77, SD = .73, N = 422) was acceptable (α = .92).

Internet health information use efficacy. To operationalize this variable, we modified 4 items from the original scale of the computer self-efficacy instrument of Compeau and Higgins.[36] Examples of these items were: (1) It is not difficult to use health information from the Internet and; (2) It is easy to learn how to find health information from the Internet. The reliability provided an acceptable Cronbach's alpha (M = 3.66, SD = .71, N = 422, α = .79).

For the purpose of validating these scales of 4 predictors of PU and PEOU, we conducted a second-order CFA through AMOS 21. We checked 3 different model-the fit indices: comparative fit index (CFI)—higher than .90—incremental fit index (IFI)—higher than .90—and a standardized root-mean squared residual (SRMR)—lower than .8. These comparative and absolute fit indices were chosen, following Hu and Bentler's suggestion.[35] CFA results validated those 4 scales (χ^2(df = 144) = 518.9, CFI = .92, IFI = .92, TLI = .90, SRMR = .06).

Perceived usefulness. To measure perceived usefulness—the extent of usefulness of a health app for managing one's health—we modified 4 items from the original scale created by Davis et al[17] to reflect use of health apps. Examples of these items were: (1) Health app(s) can be useful in managing my daily health; and (2) Health app(s) can be beneficial to me. We could get an acceptable reliability score for this measurement (M = 4.0, SD = .71, N = 422, α = .95).

Perceived ease of use. Three items from Davis et al's original scale were modified and used to operationalize PEOU, the extent to which an individual easily uses a health app.[17] Examples of these items were: (1) It will be easy to learn how to use the health app(s); and (2) Health app(s) will be easy to use. The reliability for this measurement (M = 3.89, SD = .73, N = 422) was acceptable (α = .92).

Intention to use health apps. We reworded 3 items from Davis et al's scale to operationalize one's behavioral intention to use a health app.[17] The followings are the examples of those items used for this study: (1) I intend to use health app(s); and (2) I plan to use health app(s). The reliability test provided an acceptable Cronbach's alpha for this measurement (M = 3.32, SD = .99, N = 422, α = .95).

Subjective norm. To measure subjective norm, we used 3 items that Stephens and Davis developed.[38] Examples of these items were: (1) People who are important to me think that I should use health app(s); and (2) People who are important to me inspire me to use health apps. The reliability for this measurement (M = 2.81, SD = 1.02, N = 422) was acceptable (α = .94).

These 4 factors came directly from TAM II. Thus, to validate them, we conducted a CFA for a second-order model composed of 4 factors. The CFA results showed acceptable model-fits (χ^2(df = 59) = 153.04, CFI = .98, IFI = .98, TLI = .98, SRMR = .03).

RESULTS

Attention Checks

The main purpose of the attention check was to show how carefully the research participants read and comprehended the instructions related to the 2 health apps. For this attention check, participants were required to complete 3 questions asking for specific information that was contained in the instructions. Most research participants checked the correct answer to the following attention check questions: (1) Users can budget calories for a day through "Lose It" (92.7%); (2) Through "Lose It," users can calculate calories for snacks (89.6%); and (3) Through "Runkeeper," users can calculate the amount of calories burned through an exercise (89.1%). Based on these results, we generally concluded that research participants carefully read through the installation and operational instructions.

Hypotheses Tests

To test the posited hypotheses, we conducted a path analysis that is a specific type of structural equation modeling (SEM) by using AMOS 21. Like CFA, we mainly checked 3 different model-fit indices—CFI, IFI, and SRMR. Figure 2 presented the final model without these non-significant paths. This final model showed acceptable model-fits χ^2(df = 9) = 34.2, p < .001, CFI = .97, IFI = .97, TLI = .91, SRMR = .05). Results from this path analysis presented multiple direct and indirect effects of those main predictors, supporting most o the hypotheses.

Based on TAM II, this study tested the effects of 4 major predictors on the main components—PU, PEOU, and BI—of TAM II. Although subjective norm (standardized β =.184, p < .001) and health information orientation (standardized β = .214, p < .001) positively and significantly predicted PU, health consciousness negatively and significantly predicted PU (standardized β = -.132, p = .003).

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Table 1
Correlations for Key Study Variables

		M	SD	Skewness	Kurtosis	1	2	3	4	5	6	7
1	**Health Consciousness**	3.56	.78	-.114	-.296	1						
2	**Health Information Orientation**	3.77	.67	-.358	.569	.441***	1					
3	**eHealth Literacy**	3.77	.73	-.700	1.295	.173***	.431***	1				
4	**Internet Health Information Use Efficacy**	3.66	.71	-.426	.782	.129**	.314***	.506***	1			
5	**Subjective Norm**	2.81	1.02	-.001	-.489	.109*	.188*	.122*	.163**	1		
6	**Perceived Usefulness**	4.0	.71	-.979	2.683	.048	.284***	.141**	.252***	.317***	1	
7	**Perceived Ease of Use**	3.89	.73	-.466	.471	.135**	.205***	.167**	.295***	.234***	.546***	1
8	**Intention to Use Health Apps**	3.43	1.04	-.471	-.047	.117*	.254***	.072	.118*	.577***	.527***	.344***

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The addition of these 3 independent variables—subjective norm, health consciousness, and health information orientation—into the model increased the explained variance of PU ($R^2 = .35$) to approximately 35%. This result fully supported H2 and H5; this result led to the rejection of H1.

Regarding PEOU, only Internet health information use efficacy positively and significantly predicted PEOU (standardized $\beta = .284$, $p < .001$). The effect of eHealth literacy on PEOU was negligible ($\beta = .023$, $p = .668$). Approximately 9% of the variance of PEOU was explained by 2 variables ($R^2 = .09$). These results indicated that while H3 was rejected, H4 was fully supported.

Lastly, this study tested the effects of 3 variables—subjective norm, perceived usefulness, and perceived ease of use—on behavioral intention to use health apps. Subjective norm (standardized $\beta = .463$, $p < .001$) and PU (standardized $\beta = .360$, $p < .001$) significantly affected the behavioral intention to use health apps. However, there was no significant effect of PEOU on BI ($\beta = .056$, $p = .317$). Approximately 44% of the variance of BI was explained through the addition of 3 variables—subjective norm, perceived usefulness, and perceived ease of use ($R^2 = .44$). Therefore, whereas H6 and H7 were fully supported, H8 was rejected.

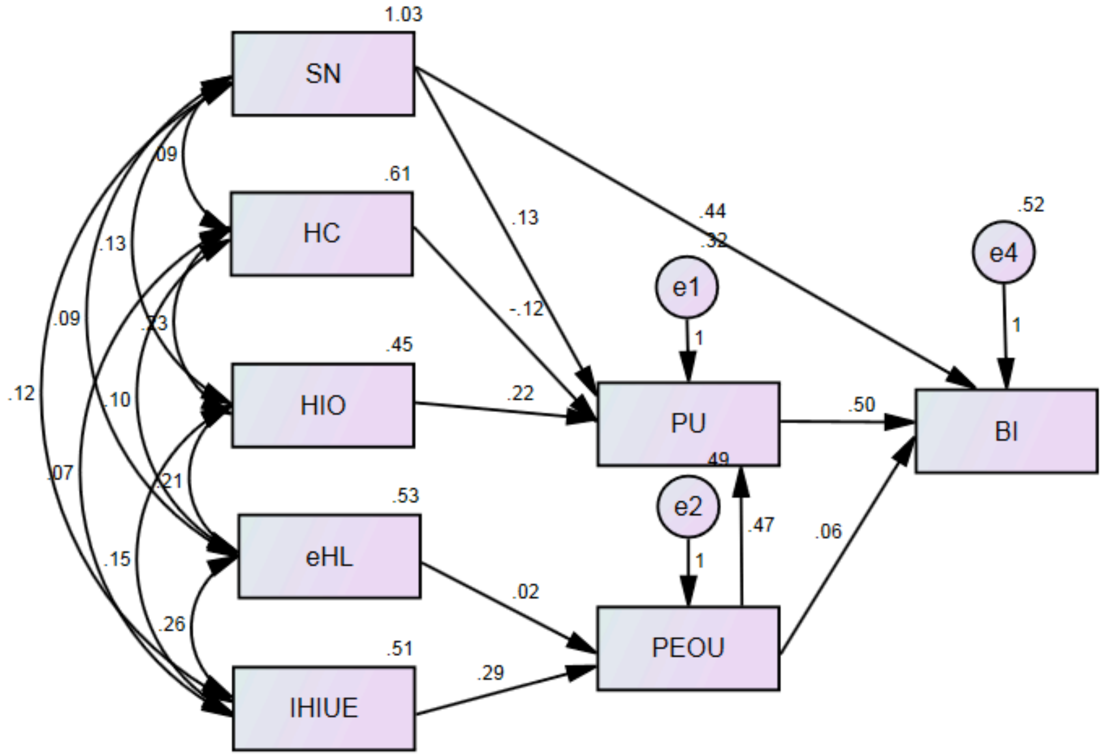
Lastly, we hypothesized the mediating effect of PU of health apps on the relationship between PEOU of health apps and the intention to use health apps (H9). SEM results presented the indirect effect of PEOU of health apps (standardized $\beta = .176$). The result from Sobel's test also supported this mediating effect of PU of health apps (Sobel's statistics = 6.81, $p < .001$), fully supporting H9.

DISCUSSION

This study aimed at developing and empirically testing a theoretical model of utilizing health apps on smart devices. Based mainly on an extended TAM, we focused attention on 5 different factors predicting PU and PEOU that eventually led to intention to use health apps. Results from a path analysis supported most of the established hypotheses. Specifically, supporting the initial predictions, these results showed that perceived usefulness of health apps was strongly associated with health consciousness and subjective norm, and that perceived ease of using health apps was significantly determined by Internet health information use efficacy. These findings will help scholars and practitioners further understand the cognitive mechanisms that drive individuals' adoption of health apps.

There were also notable findings that did not accord with originally posited hypotheses. First, health consciousness negatively affected PU of health apps. In this study, health consciousness was operationalized as the extent to which a person is aware of and takes care of her/his health condition.[27,28] Therefore, we predicted a positive association between health consciousness and PU of health apps. However, in contrast to the posited relationship, people who had high levels of health consciousness perceived health apps to be less useful. In order to understand this unexpected finding, it may be that people with higher health consciousness may possess robust routine habits of managing their own health.[27,28] Moreover, health consciousness is also often positively related to participation in a range of health activities (eg,

Figure 3
Path Model of Main Study Variables



Note.
SN = Subjective Norm, HC = Health Consciousness, HIO = Health Information Orientation, eHL = eHealth Literacy, IHIUE = Internet Health Information Use Efficacy, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, BI = Behavioral Intention to Use

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exercising, walking, health information seeking).[26] Thus, individuals with higher health consciousness in this study might have been already allocating significant resources—time, energy, and money—into various health activities. This finding could then predict that additional investment of resources for adopting health apps would lead those people to devalue the usefulness of health apps.

Another potential explanation of this unexpected finding may be related to the different characteristics of health apps vis-a-vis other online sources of health information. The main functional strength of health apps is their distribution of quality medical information, which originates from highly credible sources and is often customized for the users. However, compared to other Internet sources, especially portal websites, health apps do not provide various types of information simultaneously. For instance, users can gain access to health information and media through portal sites including news articles, blog posts, video clips, and discussion boards. This implies that individuals can evaluate and understand health information from multiple angles. In the present study, individuals who are health conscious actively take care of their health; health consciousness is also significantly correlated to eHealth literacy, as well as Internet health information use efficacy. Thus, these individuals are likely to have the capacity to find and comprehend various types of health information from diverse online sources including portal sites, professional medical sites, and others without necessarily relying on apps as their sole source of information. This also implies that those individuals would be accustomed to a breadth and depth of information that would not likely be available on apps. Consequently, it is reasonable to argue that people with higher eHealth literacy levels would perceive health apps, which are limited to single-source information, to be less useful.

Another surprising finding was the lack of relationship between eHealth literacy on the PEOU of health apps. This finding can be explained through

Table 2
Summary of Results from Path Analysis

	IV	DV	Standardized β	p-value
H1	Health consciousness	Perceived usefulness	-.132	.003
H2	Health information orientation	Perceived usefulness	.214	<.001
H3	eHealth literacy	Perceived ease of use	.023	.668
H4	Internet health information use efficacy	Perceived ease of use	.284	<.001
H5	Subjective norm	Perceived usefulness	.184	<.001
H6	Subjective norm	Intention to use health apps	.463	<.001
H7	Perceived usefulness	Intention to use health apps	.36	<.001
H8	Perceived ease of use	Intention to use health apps	.043	.317

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the displacement theory.[39] In other words, due to limited time and energy people must choose a specific communication channel, becoming less likely to use other media. Indeed, it is possible that people with higher eHealth literacy are possibly already allocating significant amounts of time and energy to search online for health information through other channels. Based on the displacement theory, this implies that such people may hesitate to adopt health apps; this is because it requires additional resources to find and process additional media. Thus, the additional effort for adopting and using another tool may exceed the usefulness and ease of use of health apps. Moreover, it should be considered that the main participants of this study were undergraduate students, a population that is known to be technologically savvy.[40,41] The process of seeking information online is a deeply embedded part of their day. Thus, undergraduate students participating in this study would have relatively similar capacity to comprehend online health information. This might have reduced the effect of eHealth literacy on PU for health apps.

Lastly, one of the main components of TAM II is the direct effect of PEOU on the intention to use. However, unlike the main claims from TAM II,[18,42] the SEM result from this study showed that there was no significant effect of PEOU of health apps on the intention to use these apps. To interpret this finding, we need to consider the overwhelming number of countless apps for smart devices. According to AppBrain (http://www.appbrain.com/stats/), which provides statistics on Android apps, the total number for Android apps downloaded in July 2013 was approximately 800,000. Of particular note, there was an increase of approximately 300,000 apps for the last 10 months. Moreover, the creation of apps is currently not just restricted to computer/software experts; ordinary people also can create their own personal apps. This ubiquity of apps in the US means that people are surrounded and overloaded by a plethora of apps for various purposes such as entertainment, games, and news. This perception of being 'overloaded' by too many apps may de-stimulate people, ultimately hindering their adoption of health apps. Moreover, although the content and ideas of health apps are new, their format is not. Because of this already-developed familiarity with apps on smart devices, PEOU may not be a critical factor in the intention to use health apps. Rather, as the SEM results showed, PEOU's effect on the intention to use health apps was mediated by PU of health apps.

Our findings include the following theoretical and practical implications. First, although there have been notable increases in the numbers of health apps and users, we have little understanding of the mechanisms underpinning health app selection and use. Lim et al's path-breaking study examined Singaporean women's adoption of health apps.[6] Although this study provided meaningful findings of understanding why women used health apps, it did not consider the predictors of PU and PEOU. Considering this limitation, this current study aimed at empirically testing a more comprehensive model based on TAM II. This study's model contributes to guiding future research to develop more complicated models with various contextual factors (eg, cultural differences, socio-economic status, gender, etc.) for accepting health apps.

Furthermore, this study can be considered as additional evidence towards proving the usefulness of the extended TAM for investigating new technological phenomena. In other words, findings from this study contribute to extending the TAM II to another new technological phenomenon of individual-level health management. Indeed, TAM and extended TAMs have previously been applied to various health-related technologies.[43] There has also been extensive research on medical doctors' and their staffs' adoption of new medical technologies.[43] Nevertheless, we have little understanding of the new trend of personalized use of health-related technologies, particularly health apps. Thus, this study expands applied TAMs into more diverse health-driven technologies, providing additional evidence of proving the usefulness of various versions of TAM.

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This study also addressed the following practical implications. In general, based on the Theory of Reasoned Action, [16] it is understandable that people who value their own health may tend to use health-related products. For example, more health-conscious people are likely to consume nutritional aids. Thus, it may be reasonable for health app companies to pay attention to these people. However, as this study revealed, more health-conscious people, especially of a younger age, may tend to give less value to health apps, potentially choosing not to use health apps. Rather, it is less health-conscious people who are likely to think that health apps are useful to improve health. This finding suggests that creators of health apps need to develop marketing strategies to target people who are less conscious of their own health.

Another practical implication is related to the finding of PEOU's non-significant effect on the behavioral intention to use health apps. Unlike the initial prediction, PEOU of health apps did not directly predict individuals" intention to use health apps. It should be noted that the average score for PEOU (M = 3.89) was relatively high. This implies that health app designers need to turn their attention to other cognitive or affective dimensions of health app uses. Based on findings from research applying uses and gratifications theory to new media uses, [44] the entertainment and communication functions of health apps will be key for more successful adoption of health apps. Particularly, those functions will be effective for attracting young populations who are already accustomed to conveniently using various other apps. For example, users of a Korean health app, "*Dieter*"—the #1 ranked free app in Google Play's "diet" category in May 2014—can communicate with other users through a virtual community that the app supports. In the online space, *Dieter* users actively exchange personal tips for their diets. Taking into account the success of this particular app, health app designers should consider convergences of the various functions of new media.

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Future Directions

Although this study produced myriad findings with application to understanding how individuals use health apps, there are fertile areas for future research on the subject First, it is noteworthy that other research has examined how demographic and socioeconomic characteristics influence people's health information seeking behavior on the Internet.[45,46] PEW research also addressed notable differences in the use of health apps among different demographic groups based on differences in age, sex, educational level, and annual household income.[5] Furthermore, studies have found preliminary evidence that literacy levels of online health information is significantly related to ethnic backgrounds.[47] Thus, productive future research may examine how differing demographic characteristics are related to disparities in health app use.

Furthermore, unlike previous research on motivations to use health apps,[6] this study expanded upon users' potential motivation using multiple predictors of 2 main components—PU and PEOU—of TAM. This is a step in the right direction; however, further research should be conducted to examine and measure the impact of other factors on health app use. For instance, future research needs to be conducted regarding social influence, including the roles of social image of health apps. Moreover, based on Venkatesh and Davis's argument,[16] we also recommend examining a potential moderating effect of people's experience using smartphone apps. Future research could extend this our model of health app adoption by including additional predictors and contingent factors.

Third, in this study eHealth literacy was measured through items which asked about individual use and comprehension of health information from the Internet. Considering the unique functional characteristics of health apps, this general measurement technique might have contributed to the non-significant effect of eHealth literacy on PEOU of health apps. A recommended suggestion for future research is: develop a new measurement for eHealth literacy, paying more attention to individuals' health information-seeking behaviors through the Internet on mobile platforms rather than through the Internet in general. This type of platform-based specificity will be helpful in examining the effect of eHealth literacy on PEOU of health apps.

Finally, there are numerous health apps for diverse purposes. However, this study provided research participants with only 2 health apps: one for exercise, fitness, and diet, and the other for weight loss. Although the underlying health goals of these health apps might be more attractive to younger populations, the selection of health apps limited the generalization of our findings to older populations and other types of apps, particularly apps specified for medical purposes (eg, Type I diabetes, blood pressure, etc). Thus, future research needs to pay attention to the adoption of other types of health apps, particularly those that may be attractive to different segments of the population. Moreover, in addition to the adoption of such health apps, it is also necessary to scrutinize potential factors that motivate current users to keep use those apps. This is related to the issue of continuity/discontinuity of using a technology, so further research on this topic will widen our knowledge of behavioral patterns of using health apps.

Conclusion

Consumers today face a dizzying array of health-related apps and features that proliferate daily. In the midst of the information overload, however, a research lacuna exists; there is little research into understanding micro-mechanisms among various motivators of consumers to adopt health apps. Thus, this study aimed at developing a theoretical model of health apps adoption, based mainly on the TAM. It analyzed potential effects of motivational predictors including health consciousness, health orientations, eHealth literacy, and subjective norm. Using an online survey, we found that the predictors played significant and meaningful roles in influencing the PU of health apps and also influencing the intent to use them.

Human Subjects Statement

Ethical permission for this study came from the University of North Carolina at Charlotte Institutional Review Board. IRB # 13-02-48.

Conflict of Interest Statement

All authors declare they have no conflicts of interest to disclose.

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