Investigation of Influential Factors of Predicting Individuals' Use and Non-use of Fitness and Diet Apps on Smartphones: Application of the Machine Learning Algorithm (XGBoost)

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Objectives: In this study, we aimed to find the influential factors in determining individuals' use and non-use of fitness and diet apps on smartphones. To this end, we focused on diverse groups of predictors that would significantly affect people's use and non-use of these apps. **Methods:** Overall, we considered 105 factors as potential predictors and included them in further analyses using a machine learning algorithm, XGBoost. The main reason for selecting this particular algorithm was that it had been known as one of the most accurate and popular algorithms for predicting consumer behaviors. **Results:** We found the accuracy score of those factors for predicting people's use and non-use of fitness and diet apps was approximately 71.3%. In particular, the most influential predictors were mainly related to social influence, media use, overeating, social support, health management, and attitudes toward exercise. **Conclusion:** These findings contribute to helping scholars and practitioners to develop more practical strategies of the implementation of fitness and diet apps.

Key words: mHealth; fitness and diet apps; machine learning algorithm; XGBoost; social influence
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Since development of the smartphone, we have consistently observed acceleration in the growth of smartphone ownership. In Korea, one of the most digitalized countries in the world, smartphone ownership already reached 90% by 2019. It is not a sufficient condition for everyday life but a necessary one. As technological and social infrastructures have been adapted to mobile technologies, all generations have become increasingly reliant on smartphones. Indeed, smartphones have become a fundamental technological component in our daily lives, and used in many ways such as lifestyle information (eg, weather, fine dust level, etc), entertainment (eg, music, movies, games), communication (eg, instant messaging, SNS), and so on. Because of the mobility and ubiquity of smartphones, they also are being applied for various health-related purposes.[1,2] For instance, research on telemedicine has addressed the usefulness of smartphones for health management for people residing in remote areas and for those who are physically limited in movement;[3] public health-related studies also have emphasized that smartphones can be used for facilitating daily health management.

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Therefore, medical engineers have placed great effort in developing various apps that help patients regularly and adequately manage their health.[4,5] For example, apps exist that support connections among patients with diabetes, caregivers, and hospitals through IoT (Internet-of-Things) technologies.[5,6] Furthermore, 'digital therapeutics (DT)' has received great attention from scholars and practitioners.[7] According to Cho and Lee,[8] digital therapeutics refer to "a new concept that encompasses therapeutic approaches that are used to change the patient's behavior using a variety of digital technologies and ultimately to treat diseases or promote health." [8(p 97)] Regarding this, it is notable that 'reSET' – a prescription digital therapeutic (PDT) developed by Pear Therapeutics – obtained the approval of the US Food and Drug Administration (FDA). Likewise, the mHealth market has expanded rapidly.

Furthermore, in the wake of the COVID-19 pandemic, mHealth is receiving increased attention from many different sectors of society, especially from the medical sector. Due to the severe impact of the virus on patients, their dependence on mHealth devices for minimizing offline interactions has increased. Governmental agencies also have been recommending that hospitals and patients use mobile tools. For example, in Korea, although telemedicine services have not been officially approved by the government, the public's demand for these services has rapidly increased. Moreover, as visits to fitness centers have been prohibited or not recommended, people have become heavily reliant on home-training services offered through various types of exercise apps. Therefore, there has been a notable increase in the market of home-training devices.[11]

Because of those technological and contextual factors, use of health apps has increased and been investigated by many studies across various academic disciplines. In spite of the large amount of research on health apps,[11,12] we know relatively little about the determinants of people's use of those apps, because most of the previous research has focused on the efficacy of newly developed apps for health. Therefore, it remains necessary to explore the potential predictors that determine people's actual use or non-use of health apps on smartphones.

One study on this topic is Cho and Kim's research.[13] Although they analyzed how various groups of factors would determine people's use and non-use of those apps, it is still necessary to: (1) include a wider range of potential factors, (2) apply a more accurate algorithm, and particularly, (3) use specific survey items based on composite measurement rather than averaged scores.

Therefore, in the present research, we aimed at analyzing how each item for measuring various groups of factors may impact people's actual use or non-use of fitness and diet apps. For this investigation, we relied on a machine learning algorithm, XGBoost, which is known as a top machine learning algorithm useful for boosting tree models, thoroughly scrutinizing each factor's unique power in predicting people's actual use or non-use of those apps. The following sections discuss major trends in mHealth and multiple sets of potential factors.

Trends and Characteristics of mHEALTH Apps

Using an mHealth app has become a popular alternative for people who want to take care of their health. Despite the high possibility that growing screen time may negatively impact our physical and mental health (eg, popcorn brain, smartphone dependency, forward head posture, etc), mHealth apps play a pivotal role in keeping us healthy. This is because smartphones act as a screens (or interfaces) that show us the status of our body. If it were not for smartphones, we would need to obtain medical charts written by physicians or make inquiries to a personal trainer about our body. Therefore, one advantage of using mHealth apps is the ease with which people can monitor their physical conditions.

The increasing use of mHealth apps is easily observable. As of 2017, more than 318,500 health-related apps had been released to worldwide consumers via Apple Store and Google Play.[14] This figure is nearly twice the number of apps available in 2015 and almost 5 times the number available in 2013. Especially in South Korea, the revenue from mobile fitness applications was $47 million USD in 2019, which is a 17.6% growth from 2018.[15] Moreover, the growth in use of health and fitness apps reached 9% in 2017, even though it is believed that the growth in apps reached critical mass.[16,17] Not only quantitative, but also qualitative growth can be found. According to the matrix that indicates royalty by app category, the health and fitness category is positioned close to or at the quadrant where both frequency and retention are high.

With regard to the means of health management, there are 3 different types of mHealth apps: apps for behavior tracking, habitual recording, and coaching. First, behavior tracking is related to the automatic detection of physical activities or bio-signals (eg, counting steps, electrocardiogram; calculating calories, moving distances, sleep hours; etc) such as "Cash Walk" and "Cash Slide – Step Up." Second, habitual recording apps (eg, "Flo Period and Ovulation Tracker") require more active efforts on the part of mHealth app users. This is because users need to record their own health-related data (eg, sleeping patterns, weight, eating habits, etc). The usefulness of habitual recording apps strongly relies on the technology of big data analysis. Based on these data, mHealth apps are able to track the cycle of body change and provide high quality solutions for good health. Third, coaching apps are designed with a focus to provide timely motivation for its users. For example, when people want to work on their abdominal muscles, "Fit Day" will show the proper clips and also encourage users to keep working out in the long run. Diet apps such as "Num" and sleeping/meditation apps such as "Kokkiri Meditation" are other examples of coaching apps.

Review of Previous Research

In this way, health apps have become increasingly popular in the realm of mHealth. Accordingly, scholars in various disciplines, including the areas of information sciences, medical sciences, and communication studies, have made intensive study of the diverse issues regarding health apps on smartphones. Among the diverse issues related to mHealth technologies, in this current research, we pursued an investigation into the factors that lead people to adopt and use health apps. For this investigation, a review was conducted of the previous studies that have examined the motivational factors for adoption or use of health apps.[18-42] A number of main themes were observed across those studies, which have been summarized in Table 1.

In terms of research topics, previous studies have explored the various groups of influential factors that determine the behavioral intentions to adopt smartphone health apps. Particularly, based on well-known theoretical models explaining technology adoption (eg, TAM, UTAUT, ECM, PAM), previous studies have focused on perceptual factors, including 'perceived usefulness', 'perceived ease of use', and so on. That is, they have analyzed how such perceptual factors influence either people's attitudes toward health apps or their intentions to adopt the apps. Another group of studies has paid attention to personality-oriented factors, including 'innovativeness', 'self-efficacy', and so on. In addition, design-oriented factors also have been considered as influential in leading people to adopt health apps. In addition to these factors, a few studies have examined the effects of body-oriented factors on behavioral intentions to use the apps. As such, previous studies have analyzed a wide range of influential factors for health app adoption.

Next, in regards to research methods, most studies have relied on quantitative research methods, especially the survey method. Meanwhile, only a small number of studies have used qualitative methods, most of which have depended on in-depth interviews or FGI (focus group interviews) to collect personal opinions from research participants.[25,29] Most of the quantitative studies had conducted either regression analyses or structural equation modeling. These analyses were useful for investigating the effects of the main predictors on intention to adopt health apps. In particular, logistic regression analysis was adequate for examining how potential predictors would affect individuals' use or non-use of health apps.

For this study, we aimed to extend the previous findings in the following ways. First, considering the wide range of determinants of health app adoption, we focused on the perceptual, emotional, body-oriented, health-oriented, demographic, and social factors. By including the diverse factors into a prediction model, we attempted to identify the relative power of the individuals predictors in leading people to use health apps. Next, in terms of analytical methods, unlike previous researchers, we applied a machine learning algorithm to analyze the accuracy of influential factors for predicting individuals' use and non-use of health apps. This was a decision based on an understanding that machine learning algorithms are known to be stronger, more reliable methodological approaches to examining causal relationships among perceptual and behav-

Table 1
Summary of Previous Research on Predictors of Health App Uses

	Author(s)	Research Methods	Predictors of Health App Uses
1	Alsswey & Al-Samarraie (2020)	Quantitative Research Methods: Survey	Perceived ease of use Attitude towards use Age
2	Alsswey et al (2018)	Quantitative Research Methods: Survey	Perceived ease of use Attitude towards use
3	Angosto et al (2020)	Meta-Analysis	Main components from TAM
4	Askari et al (2020)	Quantitative Research Methods: Survey	Attitude toward use Perceived usefulness Perceived ease of use Service availability Sense of control Self-perceived effectiveness Facilities Personal innovativeness Social relationships Subjective norm Feelings of anxiety
6	Cajita et al (2017)	Quantitative Research Methods: Survey	Social influence Perceived ease of use Perceived usefulness
7	Cajita et al (2018)	Qualitative Research Methods	Experience with mobile technology Willingness to learn mHealth Ease of use Presence of useful features Adequate training Free equipment Doctor's recommendation Lack of Knowledge regarding how to use mHealth Decreased sensory perception Lack of need for technology Poorly designed interface Cost of technology Limited/fixed income.
8	Chiu & Cho (2020)	Quantitative Research Methods: Survey	Technology readiness Perceived enjoyment Perceived usefulness Perceived ease of use
9	Chiu et al (2020)	Quantitative Research Methods: Survey	Users' satisfaction Investment size
10	García-Fernández et al (2020)	Quantitative Research Methods: Survey	E-lifestyles Perceived ease of use Perceived usefulness Attitude toward fitness apps
11	Holtz et al (2020)	Qualitative Research Methods	Existing awareness of the app Perceived usefulness Perceived ease of use Attitudes toward apps Social influence
12	Huang & Yang (2020)	Quantitative Research Methods: Survey	Personal innovativeness Network externality Habit Performance expectancy Social influence
13	Lee et al (2017)	Quantitative Research Methods: Survey	Health stress Epistemic Convenience Usefulness Reassurance Enjoyment

(continued on next page)

Table 1 (continued)
Summary of Previous Research on Predictors of Health App Uses

	Author(s)	Research Methods	Predictors of Health App Uses
14	Liu et al (2019)	Quantitative Research Methods: Survey	Performance expectancy Effort expectancy Social influence Physical activity BMI
15	Ng et al (2015)	Quantitative Research Methods: Survey	Perceived usefulness Perceived ease of use Result demonstrability Subjective norm Compatibility Facilitating conditions Security Resistance to change
16	Pai & Alathur (2019)	Quantitative Research Methods: Survey	Mobile health technology and the applications awareness Personal innovativeness
17	Park (2017)	Quantitative Research Methods: Survey	Economic level Interest Status Demographic factors Current disease Total period of smartphone use Exercise behavior Dietary management behavior Stress management Satisfaction with smartphone use Satisfaction with using health apps
18	Shemesh & Barnoy (2020)	Quantitative Research Methods: Survey	Perceived ease of use Perceived usefulness
19	Tam et al (2020)	Quantitative Research Methods: Survey	Satisfaction Habit Performance expectancy Effort expectancy
20	Yee et al (2019)	Quantitative Research Methods: Survey	Perceived usefulness Perceived ease of use Subjective norm
21	Yuan et al (2015)	Quantitative Research Methods: Survey	Performance expectancy Hedonic motivations Price value Habit Effort expectancy Social influence Facilitating conditions
22	Zhang & Xu (2020)	Quantitative Research Methods: Survey	Confirmed usefulness Confirmed ease of use Satisfaction Fitness achievement Social connection
23	Zhang et al (2018)	Quantitative Research Methods: Survey	Perceived e-health literacy
24	Zhang et al (2019)	Quantitative Research Methods: Survey	Performance expectancy Social influence Facilitating conditions Perceived disease threat Perceived privacy risk Social influence Effort expectancy

ioral variables. Other researchers also have begun to apply machine learning algorithms into predictions of psychological and behavioral outcomes in various contexts.[46-48] Based on this understanding, we pursued an examination of the accuracy of multiple factors in predicting individuals' use and non-use of health apps on smartphones. Finally, we believe that our findings will contribute to theoretically and methodologically extending the previous studies' main findings regarding the determinants of health app adoption. The following section will describe the multiple sets of main predictors.

Factors of Predicting Use or Non-use of Fitness and Diet Apps

To address the main purpose of this study, we selected multiple groups of predictors for analysis. Table 2 shows the construct components of the major factors that are known as significant ones for impacting either people's media use or health management. To explore more diverse potential factors, we included a wide range. This section provides an explanation of each group of factors.

Demographic factors. According to previous studies, media use is strongly affected by various demographic factors.[46,47] This is because people's use of media is closely related to specific motives to use, which are significantly impacted by demographic factors. Therefore, previous research has placed efforts in exploring the specific motives to use media and how they are predicted by demographic factors.[46,47] To explain this, it is helpful to discuss the demographic differences in interpersonal communication motives, because these fundamental interpersonal communication motives are closely associated with media use motives. Rubin, Perse and Barbato proposed 6 motives (eg, pleasure, affection, control, etc) for interpersonal communication, addressing the association between demographic factors and interpersonal communication motives.[48] For instance, whereas age was positively associated with affection, it had a negative relation with pleasure. Moreover, smartphone use, including app use, is also significantly associated with various demographic factors such as sex, education level, and so on.[49,50] Accordingly, we analyzed how multiple demographic factors may influence people's use and non-use of fitness and diet apps.

Media use factors. People's perceptions regarding the characteristics of a specific medium are contextually defined by personal and situational factors.[51] Particularly in terms of personal factors, individuals' experience with using a particular medium is significantly associated with their attitudes toward it. According to extended versions of the technology acceptance model (TAM), personal experience plays important roles in determining people's attitude toward a given technology, which is a strong predictor of intentions to use that particular technology.[46,47] Furthermore, according to media richness theory[48] and channel expansion theory,[52] people's experience of media use influences their perception about the richness of a given medium under certain temporal and spatial contexts. Based on these arguments from previous studies, we explored how people's use of dominant media (eg, social media, smartphone apps, etc) may affect their use and non-use of fitness and diet apps.

Health belief factors regarding lifestyle diseases. As introduced above, fitness and diet are the most popular purposes for using health-oriented apps.[9] It needs to be noted further that fitness and diet have been recognized as fundamental and critical behaviors for preventing lifestyle diseases. In addition, the Health Belief Model (HBM) argues that people's beliefs regarding specific diseases as well as preventive behaviors are influential factors in determining their intentions to conduct health preventive behaviors.[53,54] Considering these arguments synthetically, it is reasonable to hypothesize that individuals' perceptions regarding lifestyle diseases, which are mainly due to unhealthy daily habits, will be significantly associated with their intention to use fitness and diet apps. Here, use of such apps can be viewed as a preventive health behavior. Finally, in this study, we examined the association between individuals' beliefs regarding lifestyle diseases and their use or non-use of fitness and diet apps.

Exercise-oriented factors. According to the HBM, in addition to personal beliefs regarding diseases and preventive behaviors, the perceived benefits of and barriers to those preventive behaviors also directly affect people's intentions to engage in specific preventive behaviors.[53,54] For example, when a person perceives the lack of time they have for a particular preventive health behavior, s/he is less likely to initiate the behavior. Likewise, it is possible to assume that a person's perception of either the benefits of or barriers to an app-supported health behavior will influence the likelihood with which they will adopt those apps. Here, the particular app-related health behavior will be 'exercise'. Consequently, we examined the association between people's perceptions regarding the benefits of and barriers to exercise as well as their attitude toward exercise, and their use of diet-fitness apps, respectively.

Social influence factor. Individuals' attitudes toward a new technology and their intentions to adopt are often significantly affected by social influence.[55,56] The main idea of social influence is theoretically dependent on social information processing theory,[57] explaining that individuals' decision to implement a specific action is largely affected by information directly obtained through social interactions, especially from influential others close to them. Similarly, extended versions of TAM (eg, TAM II), which are theoretically reliant on the theories of reasoned action (TRA) and planned behavior (TPB), have placed emphases on the roles of subjective norms in determining attitudes toward and intentions to adopt a new technology.[57] Subjective norms can be conceptualized as influential others' opinions about a newly introduced technology. Therefore, we also examined, regarding fitness and diet apps, the association between subjective norms and use/non-use.

Weight management factors. From a functionalist approach, the main motives to use a particular medium can be instrumental;[58] that is, people are motivated to use a specific medium to achieve particular goals. An example would be an individual's use of the telephone to exchange information that is necessary for completing a given task. From this approach, weight loss will be a main purpose of using fitness and diet apps and serve as an influential predictor of diet-fitness app use. Therefore, in the present study, we investigated the association between multiple factors related to weight loss – internal health locus of control, disinhibition, diet intentions, and experience of weight loss – and people's use/non-use of fitness and diet apps on smartphones.

Body-oriented factors. Based on this idea of instrumental use, it is reasonable to argue that people's physical conditions can be directly associated with their intentions to conduct fitness and diet behaviors. In other words, a person with a high BMI (body mass index) score will be more likely to have greater interests in fitness and diet behaviors. Moreover, it is also plausible that when individuals perceives their body shape as obese, they will be more likely to engage in fitness and diet behaviors. Therefore, we analyzed the effects of multiple body-oriented factors on people's use and non-use of diet-fitness apps on smartphones.

Health condition factors. Like the potential effects of body-oriented factors on people's use and non-use of diet-fitness apps, the health conditions of individuals also can be significant factors in determining use and non-use of those apps. In other words, a person with a chronic or other diagnosed disease is likely to take positive actions to care for themselves. This implies that s/he tends to show more interests in diet and exercise that are known as basic and necessary actions for overcoming health damages. Therefore, we also explored how health conditions would potentially predict people's use and non-use of fitness and diet apps.

Psychological factors. Previous studies have extensively observed the association between media use and various psychological variables. Although there exist numerous psychological factors related to media uses, we paid attention to the following, mainly considering the major motives for media use: social isolation, social support, subjective well-being, and self-esteem. As noted above, one reason people use media is to be connected with others so as to share useful information as well as to give and receive emotional support. Accordingly, according to Bochner,[59] 2 major motives for using media are 'persuasion' and 'expression of affection'. Considering these points, we selected social support and social isolation as psychological factors potentially associated with people's use of diet-fitness apps on smartphones. Moreover, because of people's heavy, daily dependence on various media, media use is often strongly associated with self-esteem [60] and subjective well-being.[61] It is plausible that people with higher levels of self-esteem and/or subjective well-being will tend to care for themselves more (by way of using diet-fitness apps, in this study) to maintain or increase their quality of life. Therefore, we examined the associations among these 4 psychological factors and use of diet-fitness apps.

In this way, the main goal of this research was to identify the specific factors that predict people's use or non-use of diet-fitness apps. In addition, another goal was to examine the relative strength of effects among the predictors. The final goal of this study was to examine the prediction power of those detected factors. For this investigation, the following 2 research questions were developed and explored by using machine learning algorithms.

RQ1: Which factors will play significant roles in determining people's use and non-use of fitness and diet apps on smartphones?

RQ2: How accurately will the proposed factors predict people's use and non-use of fitness and diet apps on smartphones?

METHODS

Data Collection

To explore the 2 research questions, we used cross-sectional data from an online survey collected by a health communication research center situated in a large Korean university, which houses undergraduate, graduate, and professional schools. A research company with the largest pool of panels was responsible for conducting data collection. The whole survey was comprised of items whose topics mainly focused on: (1) health belief model (HBM) and fitness and diet app uses, (2) evaluation of public campaigns for stopping smoking, and (3) breast cancer and psychological conditions. The primary researcher, who was a member of the research institution, selected and used specific items that were more closely related to people's use of fitness and diet apps on smartphones. Surveys with any missing data were removed from further analyses. In total, 1497 usable surveys were collected and used for this study. To heighten the representativeness of the samples, 3 demographical factors (sex, age, and residential areas) were considered. There were slightly more male participants (male: 51.1%, female: 48.9%), and the average age of those participants was 44 years. Most of survey participants (97%) had high school or higher degrees, and their median monthly income was \$2000~\$3000. According to 2018 statistics from the Korean Statistical Information Service (KOSIS), among the 25-64-year-old population in Korea, 88% had held high-school or higher degrees.[62] In addition, KOSIS reported the average annual income for 2018 to be at approximately \$2800.[63]

Measurements

To check individuals' use and non-use of fitness and diet apps, survey participants were asked whether they were currently using fitness and diet apps on smartphones. Moreover, as noted above, to identify as many influential predictors as possible, we attempted to address diverse groups of factors. Table 2 indicates the following information: (1) names of conceptual constructs, (2) names of factors, (3) number of survey items for composite measurements (5-point Likert type scales used), and (4) sources of survey items. In total, 105 variables were used for further analysis. Because this research did not create a composite variable using an average score of multiple items, Cronbach's alpha for each of composite measurements was not calculated. Rather, each of all survey items was considered as a unique predictor. This was mainly because of the algorithm we selected relies on the integrative evaluation of results from randomly selected sub-samples. This means that internal consistency reliability of multiple items for a composite measurement continues to generate change. Therefore, we considered each survey item as a separate and unique predictor. Finally, a considerable contribution of this research should be that it provides scholars with the guidance of removing redundant items for measuring a factor, shortening the research survey.

RESULTS

Priority Analysis Method

For applying the machine learning algorithm, the whole sample was randomly divided into either a train set (80% of the whole sample) or a test set (20% of the whole sample). After creating the train set and the test set, we conducted further analysis through the following 3 steps.

First Step: Machine Learning Model Selection

There are several machine learning models for prediction such as RandomForest, LightGBM, Adaboost XGBoost that have their own advantages and disadvantages. To choose the suitable leaning model, we referred to the Kaggle site.[64] There were 29 challenges at Kaggle in 2015; XGBoost was used for core learning model for the 17 winning solutions of them. The main problems in the 17 winning solutions are related to customer behavior prediction, and store sales prediction, which is

Table 2
Scales for Measuring Groups of Potential Predictors

Demographical factors	Residential areas Sex Age Educational level Monthly income
Media use factors	Extent of using social media Frequency of using social media Use/non-use of apps on smartphone Number of currently-using apps on smartphone Frequency of currently using apps on smartphone
Factors about health beliefs in lifestyle diseases	Perceived susceptibility (5 items, Lee et al, 2012) Perceived severity (5 items, Lee et al, 2012)
Exercise-oriented factors	Benefits of exercise (8 items, Lee et al, 2012) Barriers against exercise (7 items, Lee et al, 2012) Attitudes toward exercise (6 items, Lee et al, 2012)
Social influence factor	Subjective norms about fitness and diet apps (3 items, Venkatesh & Davis, 2000)
Weight-management factors	Internal health locus of control (8 item, Wallston et al, 1978) Disinhibition (10 items, Kim et al, 2003) Dietary restraint (8 items, Kim et al, 2003) Experiences of weight loss
Body-oriented factors	BMI Perceived body shapes
Psychological factors	Social isolation (4 items, Hawthorne, 2006) Subjective well-being (6 items, Diener, 1994) Social support (5 items, Barrera, Sandler, & Ramsay, 1981) Self-esteem (4 items, Robins, Hendin, & Trzesniewski, 2001)
Health conditions	Smoking/non-smoking Having chronic diseases Diseases diagnosis for last 5 years

identical with our purpose in this study.[65] Therefore, because we paid attention to people's behaviors of using or not using a product, XGBoost was adopted for this study.

Second Step: Hyperparameter Tuning by GridSearchCV

To avoid overfitting as well as optimizing the hyperparameter of XGBoost,[64,65] we proceeded KFold-cross-validation (CV) with GridSearch, and the number of k was 10 folds based on the guidance from Arlot and Celisse.[66] In more details, the CV randomly divides the trained data set into the subsets of k (ie, 10) folds and then calculate mean prediction accuracy of them. Finally, the mean prediction accuracy is compared with that of the accuracy of test set. If the accuracies are similar to each other, it is considered that there is no overfitting in this XGBoost. After cross-validation, the hyperparameters of Gridsearch are optimized by substituting all possible numbers with a brute force method.

To satisfy the main purpose, to prioritize the Influential factors, Gridsearch is employed because the accuracy is a crucial factor. As a result, the mean accuracy score in Gridsearch is 0.76975 (77%) with the std accuracy score of 0.026791. The accuracy score for the test set is 0.713. Therefore, KFold-cross-validation (CV) with GridSearch validated that there is not overfitting in this XGBoost.

Third Step: Find Influential Factors

In this step, we tried to prioritize the influential

Table 3
Top 20 Influential Predictors

Rank	Name of Construct	Name of Factor	Information Gains (%)
1	Social Influence	My influential others (eg, family, friends, colleagues) encourage me to use fitness and diet apps	6.314652756
2	Social Influence	My influential others (eg, family, friends, colleagues) recommend that I use fitness and diet apps	5.391674762
3	Media Use	Frequency of social media use	2.894856766
4	Disinhibition	I eat a lot when a neighbor overeats	2.878062727
5	Media Use	Number of currently-using apps on smartphones	2.637276368
6	Social Support	Social Support: I have people who shows deep affection to me.	2.578916405
7	Attitude toward Exercise	I am responsible for regularly exercising to manage my health	2.380427184
8	Social Influence	Social Influence: My influential others (eg, family, friends, colleagues) believe that I must use fitness and diet apps	2.362601828
9	Health Management	Voluntary regular exercise	2.291755744
10	Health Management	Weight management	2.142831247
11	Health Management	Voluntary diet management	1.784516717
12	Disinhibition	If I smell favorite foods like roasted meat or fish, I try to eat them even if I am not hungry	1.666950592
13	Perceived Barriers Against Exercise	I think regular exercises are not very helpful for preventing life-style diseases	1.619399157
14	Perceived Benefits of Exercise	Regular exercise will guarantee a healthy life in my later years	1.585837562
15	Social Support	I have close people with who I share happiness and sadness.	1.581671181
16	Attitude toward Exercise	It is important to maintain my health condition while I am in good health	1.518888452
17	Demographical Factor	Education level	1.501293141
18	Demographical Factor	Monthly income	1.480555195
19	Perceived Barriers Against Exercise	I do not think I can financially afford to exercise regularly.	1.465355152
20	Internal Health Locus of Control	It is up to my behavior that my weight decreases or increase	1.447405372

factors by using the tuned XGBoost model from the second step. We used the information gain method in the research of Guyon and Elisseeff to identify the precedence of the influential factors among 105 factors.[67] Table 3 reveals the top 20 influential factors to identify the primary influenced factors for the personal and social predictors of use and non-use of fitness and diet apps on smartphones. As Table 3 shows, diverse factors played key roles of predicting people's use and non-use of fitness and diet apps on smartphones. According to the results, top 5 predictors were associated with 'social influence', 'media use', and 'disinhibition.' Expanding those influential predictors to the top

10 ones, 'social support', 'attitude toward exercise', and 'health management' also were strongly associated with people's use and non-use of fitness and diet apps on smartphones.

DISCUSSION

We tried to investigate potential factors that would play significant roles of determining people's use and non-use of fitness and diet apps on smartphones. Unlike previous studies, we paid major attention to finding factors for significantly predicting people's actual 'behavior' to use or not use those apps, not their intentions of doing so. Because there has been little research on thoroughly examining and estimating the accuracy of potential predictors, our main findings provide scholars with empirical evidence of explaining various factors' roles in determining people's use and non-use of fitness and diet apps – particularly the points identified below.

First, social influence played a critical role in predicting people's use and non-use of fitness and diet apps on smartphones. As noted above, it is well known that people's decision to adopt and use a new technology is strongly influenced by subjective norms.[47] This is mainly because according to *social learning theory* and *social information processing theory*, people gain important guides for their behaviors through social interactions. Moreover, information from influential others is more likely to be progressed through a heuristic system rather than through a logical one. For example, parental guides are often spontaneously and heuristically accepted by children, without logical progression of information. In this way, the prediction power of influential others' opinions for determining people's behaviors of using a technology could be reconfirmed through this research.

Another considerable finding from this research was that social support was a statistically significant factor of determining use and non-use of fitness and diet apps. This would be mainly because of the positive relationship social influence and social support. That is, it is possible that people with a higher level of social support are more reliant on others with close relationships. Moreover, it is also plausible that people are likely to show higher level of reliability to others who provide social support. This finding reconfirms that people's adoption of a new technology is associated with a wide range of psychological factors. Nevertheless, previous research has paid relatively little attention to psychological factors (ie, group-oriented psychological factors such as group attachment, organizational support, etc) that would indirectly impact people's technology adoption. Finally, future research needs to examine how various factors, those that determine group or organizational norms, impact people's actual use or non-use of a new technology.

These findings were theoretically and practically meaningful in the following ways. First, our main findings can be applied to developing theoretical models that investigate people's behaviors of using fitness and diet apps, thereby providing researchers with empirically-supported guidance in selecting more powerful predictors of such behaviors. In other words, based on our main findings, future research will be able to create simple but powerful models that include indispensable factors. The relatively small number of powerful factors will enable model parsimony.

Moreover, practically speaking, in addition to the construction of a concise model, ourin findings should help researchers shorten the lengths of their surveys. This is because, unlike previous studies,[8,13] the current study considered each survey item in a composite measure as a separate and unique predictor, allowing the identification of the particularly influential items within a survey. It will be efficient for future research to include mainly those items proposed in this research, rather than using the entire set of items for a composite measure.

In this way, this study provides scholars and practitioners with multiple meaningful findings. However, the following limitations need to be considered. First, to improve prediction accuracy, it is necessary to increase the sample size. In particular, we recommend that future research enlarge the size of the train set. Next, to discuss 'causality', it is also necessary to conduct a longitudinal study by collecting data at multiple temporal points. We particularly recommend a time-series analysis for more thorough investigation of the causal relationships between the main predictors we detected and individuals' future behaviors of either adopting or continuing to use fitness and diet apps. In other words, data collected through a panel study would be useful for gaining more prediction power for those influential predictors we identified.

Human Subjects Approval Statement

This study did not involve original data collection involving human subjects.

Conflict of Interest Disclosure Statement

The authors have no conflicts of interest to declare.

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