Tracking and Modeling Subjective Well-Being Using Smartphone-Based Digital Phenotype

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ABSTRACT

Subjective well-being (SWB) is a well-studied, widely used construct that refers to how people feel and think about their lives as one of many comprehensive perspectives on well-being. Much research has analyzed the role and utilization of technologies to improve one's SWB; however, especially when it comes to user modeling, multifaceted and variational aspects of SWB are less frequently considered. This paper presents an analysis on identifying factors for smartphone-based data on SWB and modeling SWB changes, based on a four-month user study with 78 college students. Our regression analysis highlights the significance of user attributes (e.g., personality, self-esteem) on SWB and salient factors derived from smartphone data (e.g., time spent on campus, ratio of standing/sitting stationary, expenses) that significantly account for SWB. Our classification analysis shows the potential for detecting SWB changes with reasonable performance, as well as for improving a model to be more tailored to individuals.

CCS CONCEPTS

• **Human-centered computing → User models**; **Ubiquitous and mobile computing**.

KEYWORDS

Subjective well-being, positive computing, smartphone-based digital phenotype, user modeling

ACM Reference Format:
Soyoung Rhim, Uichin Lee, and Kyungsik Han. 2020. Tracking and Modeling Subjective Well-Being Using Smartphone-Based Digital Phenotype. In *Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '20), July 14–17, 2020, Genoa, Italy.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3340631.3394855

1 INTRODUCTION

Subjective well-being (SWB) is defined as the quality of life experienced by people, which includes both emotional reactions and cognitive judgments. Research in behavioral sciences and psychology has emphasized the importance of SWB in many life domains (e.g., home, social, workplace) [46]. Having high SWB generally leads individuals to feel positive about life, behave positively, have high self-esteem, and pursue strong social bonding activities [52]. Furthermore, it strongly relates to social capital, externalizing social support, trust, reciprocity, and community engagement [37]. Such impacts of SWB on individuals and societies have motivated research in many areas, especially in the context of our interactions with information communication technologies (ICT). This so-called *positive computing* [9] research has explored many related topics, such as the current practice of ICT use and its role in SWB [10], various psychological factors affecting SWB through ICT use [6].

As smartphones gain widespread adoption, showing high user engagement and providing rich data, people's life patterns are increasingly reflected in the data collected from their smartphones. This emphasizes the smartphone as an important new research tool for understanding one's psychological aspects [35]. Accordingly, researchers have started to identify and demonstrate various behavioral markers related to smartphone users' SWB components (e.g., happiness, life satisfaction, depression) through passive smartphone sensing [31, 44, 54], known as *digital phenotyping* [22]. Many study results have revealed that digital phenotypes are closely related to users' psychological well-being. With the recent advance of machine learning and deep learning techniques, studies on developing regression or classification models based on smartphone usage data for predicting a user's SWB components are now actively underway.

Theoretically, SWB is a broad category of phenomena that consists of *positive* (life satisfaction, pleasant effects) and *negative* (unpleasant effects) components [12, 50]. However, such a multifaceted concept of SWB is less developed in research. Mainstream studies have been concerned with only a single aspect, such as negative emotions or psychological disorders [1, 4, 8, 23, 51, 53, 56]. Because of the mutual relationships between SWB components, they need to be considered together to better understand and find ways of supporting SWB. This is important because research has highlighted the roles of positive emotions/thoughts/behaviors, not only to support beyond-intrinsic enjoyment, but also to help regulate negative feelings and their side effects (e.g., low health/mental conditions, low productivity). From the perspective of such an *undoing effect* [17, 28], we consider both negative and positive aspects of SWB in our research.

For improving SWB from an integrated perspective, we looked for salient factors of SWB changes and appropriate feedback by tracking changes through a regression analysis. We also looked into the temporal characteristics of the data and their effect on SWB changes through a classification perspective to better capture a group of trends (i.e., increase, decrease, and no change) in SWB,

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UMAP '20, July 14–17, 2020, Genoa, Italy

ACM ISBN 978-1-4503-6861-2/20/07…$15.00
https://doi.org/10.1145/3340631.3394855

Ref	Condition	Study Type	Main Result	Sensors Used	# Users	Duration
[1]	Bipolar disorder	Classification (SVM)	85% (Precision, binary)	Accelerometer, Call logs, SMS, Light	7	4 weeks
[4]	Bipolar disorder	Correlation	Correlation between sensor data and bipolar disorder	Accelerometer, Call logs, SMS, GPS	13	48 weeks
[18]	Bipolar disorder	Regression (Linear regression)	0.40 (Average MAE) from -3 to +3	Accelerometer, Call logs, GPS, Screen time	10	52 weeks
[20]	Bipolar disorder	Classification (Naïve Bayes)	1. Recognition : 80% (Accuracy, 7 classes) 2. Detect change : 96% (Precision, binary)	Accelerometer, GPS	12	12 weeks
[21]	Bipolar disorder	Classification (Naïve Bayes)	1. Recognition : 76% (Accuracy, 7 classes) 2. Detect change : 97% (Recall, binary)	Accelerometer, Call logs, GPS, Sound	10	12 weeks
[5]	Stress	Correlation	Correlation between sleep and stress	Accelerometer, GPS, Light, Microphone	47	10 weeks
[7]	Stress	Classification (Gradient boosting)	71% (Accuracy, binary)	App usage, Calls, SMS	117	8 weeks
[19]	Stress	Classification (Decision tree)	71% (Accuracy, 3 classes)	Accelerometer	30	8 weeks
[38]	Stress	Classification (Logistic regression)	55% (Accuracy, 3 classes)	Accelerometer, Address book, Battery, Calls, Calendar, GPS, Microphone	35	16 weeks
[49]	Stress	Correlation	Correlation between sensor data and stress	Accelerometer, App usage, Calls, Device activity, SMS Light sensor, Microphone	15	2 weeks
[3]	General mental health (Mood)	Regression (Stepwise regression)	0.41 (Average MAE) from -2 to +2	Accelerometer, App usage, Calls, SMS, Screen time, Phone camera events	33	6 weeks
[8]	General mental health (Happiness)	Classification (Random Forest)	80% (F1-score, 3 classes)	Call logs, SMS, Bluetooth	117	8 weeks
[23]	General mental health (Happiness)	Classification (Random Forest)	70% (F1-score, binary)	Accelerometer, GPS, App usage, Calls, SMS	66	4 weeks
[33]	General mental health (Mood)	Classification (Random Forest)	80% (Accuracy, 5 classes)	Accelerometer, Calls, GPS, SMS, Microphone, Light	15	4 weeks

Table 1: Summary of mental health studies, ordered by condition (bipolar disorder, stress, and general mental health). We focused on study type, main result, sensor used, number of users, and duration.

which is useful to provide timely and appropriate feedback and to articulate how undoing effects can play a role in balancing SWB. In other words, depending on their SWB status, proper suggestions can be made to a user. When an SWB decrease is detected, features that account for such a decrease can be considered and controlled. For example, if a factor, "time spent on campus," derived from location sensor data, is found to be negatively related to SWB, the smartphone can recommend a new, user-relevant activity/event held beyond campus limits.

In our research covered in this paper, we used various types of passive smartphone sensing data (e.g., activity logs, applications, locations) and SWB responses collected from 78 college students over one semester (four months). Our study results highlight the following:

- Our hierarchical regression analysis results reveal the significant influence of user-inherent attributes (e.g., self-esteem, psychological capital, depression, personality) on SWB.
- We identify salient factors derived from passive smartphone sensors and usage data on SWB changes (e.g., time spent on campus, ratio of standing/sitting stationary, expenses, app usage, and phone usage time), which can be used to define proper feedback to users.
- As SWB greatly depends on individuals, we develop a classification model that predicts SWB changes for each participant. The model performance also varies by participants, and we found the max F1-macro score was 71% (the average F1-macro score for all users was 38%). This implies the potential of smartphone log data to be used to track a specific time frame (which works better to active smartphone users than less active ones), such as the point in which SWB is decreasing. It can then be used to generate proactive intervention that better manages one's SWB.

The rest of the paper is organized as follows. First, we discuss prior related work, especially on the association between mental health and passive smartphone sensor data, detecting mental health states, and digital phenotype research on students' well-being. We then present an overview of our user study and details on the data collection. Next, we present a list of features used in regression and classification modeling, as well as the results of each modeling. Lastly, we discuss our results and conclude with future study directions. We believe that our study results not only substantiate perspectives discussed in prior research but also extend the utilization of smartphone capabilities as a way to support one's SWB.

2 RELATED WORK

The management of mental health through smartphone-based passive sensing and capturing mental health information (e.g., status, symptoms) is a topic that has gained much attention and interest in pervasive health care. Types of smartphone sensors include accelerometers, call logs, light monitors, screen time monitors, microphones, battery monitors, phone cameras, applications, SMS, GPS, etc. Regarding mental health, our literature review particularly focused on three mental conditions (i.e., bipolar disorder, stress, happiness, and mood; we realized that little research has considered SWB as a dependent variable). As summarized in Table 1, we observed two types of research directions in this domain: *association* and *prediction* (detection and/or forecasting).

2.1 Association between mental health and passive smartphone sensor data

Prior studies in this direction focused on finding a correlation between mental health and collected smartphone sensor data. Based on the correlated results, these studies provided and discussed analytical understandings and insights on the parameters that influence the status of mental health [4, 5, 30, 49]. Related studies analyzed sensor data to investigate whether passive smartphone sensor data can be employed to predict or measure the status of mental health. Some findings include (1) significant correlations between the levels of stress and noise exposure, social contacts, location, and sleep, (2) a negative relationship between depressive symptoms and social communication, and (3) a positive relationship between levels of physical activity and happiness. These findings show the possibility of measuring mental health based on smartphone data.

2.2 Detecting state of mental health based on smartphone passive sensor data

Prior studies on building a predictive model aim to detect/recognize current mental states based on real-time and/or previous passive smartphone sensor data. These studies mainly used features including physical activity (e.g., standing/sitting stationary, walking, running, driving), location (e.g., total distance traveled during the day, changes in location, significant places visited), and smartphone usage (e.g., call duration, SMS, app usage). Based on these types of features, studies employed statistical and machine learning models (e.g., Linear Regression, Naïve Bayes, Random Forest) to recognize user mental health states [1, 3, 5, 7, 8, 18–21, 23, 33, 38]. They mainly focused on binary classification (e.g., having bipolar disorder or not, having stress or not) and used several evaluation metrics (e.g., mostly accuracy and F1-score, with some using precision and recall), presenting a wide range of model performances (from 55% to 97%), which depend on users, number of classes, and contexts. Studies on regression analysis focus on a degree of mental illness as a continuous variable and presented reasonable performance, showing around 0.40 average mean absolute error (MAE) for a scale of 4-6.

2.3 Technology for students' well-being

Our study deals with college students' subjective well-being. Students are one of the main populations who suffer from various mental illnesses (e.g., stress, depression, social isolation). Not surprisingly, much research has been conducted to examine the individual, social, and technological factors of such diseases and to find ways of mitigating them through a better utilization of technology. For example, in the case of smartphone technology, Wang et al. [56], using smartphones and wearable devices, conducted a nine-week study of 83 college students and found correlations between symptoms of depression and smartphone use and wearable passive sensor data. They demonstrated that students with high PHQ-9 scores (Patient Health Questionnaire; a depression scale) were more likely to use their smartphones in study places (e.g., classroom, library). The StudentLife project [55] demonstrated a relationship between passive sensing behaviors from smartphones, such as activity and co-location, conversation, and sleep, with mental health outcomes, including stress, loneliness, and depression for 48 college students. Lane et al. [29] presented a mobile application, "BeWell," which monitors user behavior along three health dimensions (i.e., sleep, physical activity, and social interaction) and provides feedback for each dimension based on the logs kept by individuals.

2.4 Our research contributions

Our literature review highlights many efforts to investigate mental health through the analysis and modeling of passive smartphone sensor data. However, we realize that there is a lack of investigation on SWB as a case of mental health, considering both positive and negative aspects (even though a significant influence of SWB on individuals and societies), its changes, and the factors that account for such changes. Understanding SWB based only on a specific time point is somewhat limited because of the temporal continuity and variation aspect of SWB. This emphasizes the importance of not only finding increasing and decreasing trends from the default state based on last days and but also extracting factors of overall aspects in well-being, which will be used to support improving one's well-being when needed. For example, trends can be used to help increase well-being when one's SWB decreases, acting as undoing effects by capturing factors that account for the SWB decrease. Hence, we focus on analyzing patterns of SWB with the following objectives: (1) identifying salient factors that influence SWB and (2) predicting SWB changes based on such factors.

3 USER STUDY PROCEDURE

Figure 1 illustrates the overall process of our research. Our primary goal is to support improving people's SWB via smartphone-based data. To do this, we developed a smartphone application to collect

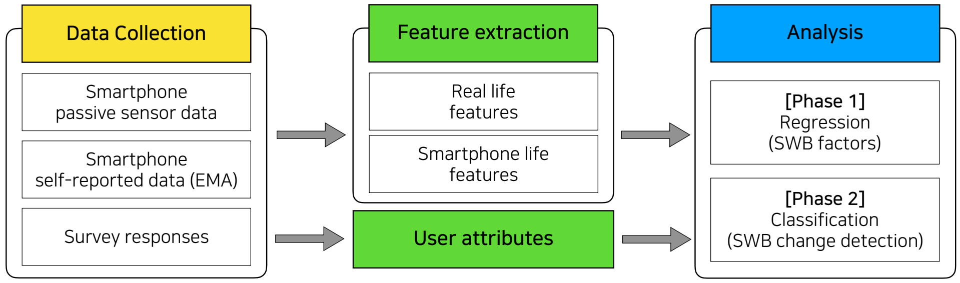

Figure 1: Overall process of our research, consisting of data collection, feature/user attribute extraction, and analysis/modeling.

passive sensing and self-reported data with an ecological momentary assessment (EMA) approach [48]. EMA involves repeated sampling of subjects' current behaviors and experiences in real time in the subjects' natural environments. It aims to minimize recall bias, maximize ecological validity, and allow the study of microprocesses that influence behavior in real-world contexts. Using this smartphone application, our research consists of data collection done through a user study, followed by feature extraction, data modeling and analysis, and discussion.

We conducted a four-month (9/10-12/17, 2017) user study in the wild. We originally recruited 86 participants who were first-year students and Android users. We invited participants to our research laboratory, where we explained the overall goal and procedure of the user study and answered any questions from the participants. We also obtained participant permission before proceeding further. We did not collect any user-identifiable information (e.g., participants' names, home addresses, etc.; geo-coordinates were not converted to actual addresses). Our study was approved by the author's university Institutional Review Board (IRB).

After the study orientation, we asked participants to complete a pre-survey that asked for their demographic information, including age, gender, Rosenberg's Self-Esteem Scale (RSE) [42], Positive Psychological Capital (PPC) [32], Patient Health Questionnaire (PHQ) [25], Smartphone Addiction Scale (SAS) [27], and the Big Five Inventory (BFI: Openness, Conscientiousness, Agreeableness, Extraversion, Neuroticism) [24] which are found to pertain to one's well-being [11, 12, 16, 26]. Our intention for collecting such user attributes information was to control them [13], when building a statistical (regression) model that considers the relationship between passive smartphone sensing data and the degree of SWB (note that age was excluded in the regression analysis because most participants were in their 20s). After the pre-survey, each participant installed the application. We showed each participant how to respond to the mobile EMA system when the EMA prompt is displayed. Only the participants who understood the research procedure and agreed to participate could start the study. Participants who completed the study received $100 for their time.

Seventy-five participants started their data collection on September 10th (for 14 weeks), and the remaining 11 participants started on September 22nd (for 12.3 weeks). Eight participants dropped out, leaving a total of 78 participants completed the study. The reasons for dropouts included data collection burdens (n=6), smartphone changes (to the iPhone) (n=1), and leaves of absence (n=1). Fifty-six (71.7%) were males, and the average age of participants was 19.6

[Part 1] life satisfaction The following are questions about your life satisfaction. Three important aspects of our life are the personal (e.g., achievements, personality, health), relational (how I get along with others), and collective (groups or organizations that I belong to – work, community) domains. Please think about each area, and rate how satisfied you are with each of the domains. Please select a number from 1 ("strongly disagree") to 7 ("strongly agree") that best reflects your thought.
(Q1) I am satisfied with the personal aspects of my life. (Q2) I am satisfied with the relational aspects of my life. (Q3) I am satisfied with the collective aspects of my life.
[Part 2] Emotional experience The following are questions about your emotional experience. Think about the events and thoughts you had in the last couple of days, and rate how frequently you have experienced each of the following emotions during this period. Please select a number from 1 ("never") to 7 ("always") that best reflects your experience
(Q4) Joyful (Q5) Happy (Q6) Peaceful (Q7) Irritated (Q8) Negative (Q9) Helpless

Table 2: COMOSWB questions answered through EMA.

(standard deviation was 0.6). The skewed gender distribution was due to the fact that the study was conducted at a large technical university where about 70% of the students are male. We used our web-based portal to track the data collection status by checking the last data sync times. If data was missing for longer than one day, then we worked with the affected participants to resume data collection.

4 DATA COLLECTION

4.1 Self-reported data (subjective well-being)

To measure participants' SWB, we used Concise Measure of Subjective Well-Being (COMOSWB), which is a SWB scale that takes into account both positive and negative components of SWB [50]. COMOSWB consists of a total of nine questions (Table 2) with two major parts. Questions 1-3 in the first part are pertinent to one's life satisfaction, and Questions 4-9 in the second part ask about one's emotional experiences. A detailed description of each part was given to the participants before they answered the questions. Responses to the questions were collected every day.

4.2 Smartphone passive data

Smartphone usage and sensor data collection were implemented based on Android's accessibility service, which helped us collect

Data type	**Description**
Activity	Activity class in every 15s (i.e., Still, Walk, Run, Bike, Vehicle)
Application	Running apps
GPS	GPS location in every 5s if activity is not still
Notification	Notification source, title
Screen On/Off	Screen On/Off event

Table 3: Smartphone usage and sensor data collected.

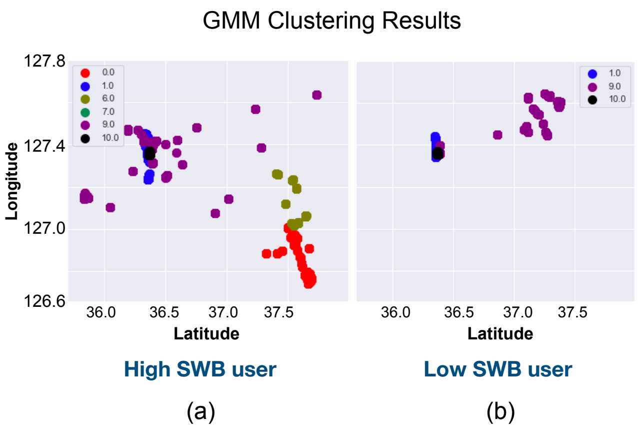

Figure 2: Examples of GMM results. Each cluster represents a location based on GMM. (a) A user with a high SWB score (mean: 34.5) tends to move more and have more clusters than (b) the one with a lower SWB (mean: 10.2). Same insight can be found in Table 4.

interaction and sensor data in the background. Data types included measurements of physical activity (e.g., walking, running, in transit, moving/not moving), GPS (latitude and longitude if moving, sampling every 5 seconds), apps (names of those being used), screen status (on/off), and timestamps. Our app temporarily stored all collected data as an SQL file in each phone's local directory. Stored data was then transferred every six hours when connected to a Wi-Fi network in order to minimize cellular data transfers. Table 3 summarizes a list of passive sensing data. Using the insight shown in Table 1, we extracted two feature perspectives: *real life* and *smartphone life.*

5 FEATURE EXTRACTION

5.1 Data pre-processing

In order to scale features prior to extracting activity, location, and app usage data for participants, we mapped the collected data to minutes and calculated ratios of time spent in specific locations, ratios of duration for specific activities, and ratios of specific app usage. We present our rationale for feature selection and detail each feature in the following subsections.

5.2 Real life features

Real life features consider the data that reflects people's actual daily life, such as locations (e.g., location change, time spent on campus), sleep times, and user activities (i.e., moving or not moving).

5.2.1 Location change. We calculated the total distance traveled during the day by using the haversine library in python. [1] Location can be represented by two main features as follows. We employed Change in Displacement Representation (CDR), which was designed to extract location-related features from various studies [34, 43]. The total number of movements between clusters was calculated by clustering the location with a Gaussian Mixture Model (GMM) [41]. We had GMM generate 10 clusters for each participant. The advantage of GMM over K-means is that GMM results in soft clustering. A limitation of K-means is that there is no uncertainty measure or probability that tells us how much a data point is associated with a specific cluster; GMM, by contrast, has greater flexibility.

Figure 2 illustrates an example of GMM. Each cluster with a different color represents a location (note that although we set GMM to generate 10 clusters maximum, the cluster number varies by participant). (a) A user with a high SWB score tends to move more and have more clusters than (b) the one with a lower SWB. To prepare the features that apply to all participants for regression and classification modeling, we grouped the clusters based on whether the cluster was within a campus or outside campus location; this information was based on whether the distance from the center of the university was within 1 km.

5.2.2 Time spent on campus. We considered the university to be a place that affects participants' SWB. Thus, based on the GMM results, we calculated the ratio of daily in/out university time to determine whether the amount of time a person stays at university affects their SWB. We normalized the ratio of in/out university time by using min-max normalization.

5.2.3 Total sleep time (sleep time representation). We utilized participants' phone screen status data as well as activity log data. We applied a simplified version of the method introduced by Abdullah et al. [2] as follows. All non-usage periods during the potential bedtime period (10PM-10AM) were detected based on screen on/off patterns. A non-usage period starts from the time the phone screen turns off until it turns on again. There are times that screens turn on without any action from the user, an event primarily caused by notifications. To ignore such negligible periods of time, we established a 1-minute time lag threshold to merge these consecutive non-usage periods. We also considered the user to be in a sleep status if the time lag between the two consecutive non-usage periods was above the mentioned threshold, even though the user's activity was still based on the activity log. Our justification for this is that a user may temporarily wake up and interact with their phone very briefly (e.g., checking the time) before going back to sleep again. Our algorithm then identifies the longest non-usage period as the sleep duration from which sleep onset and wake-up times can be easily extracted.

5.2.4 Ratio of stationary behaviors. Research has found that happier people generally move around more than less happy people [30]. Hence, we calculated the daily percentage of moving (and not moving) and normalized the percentage using min-max normalization.

[1] https://pypi.org/project/haversine/

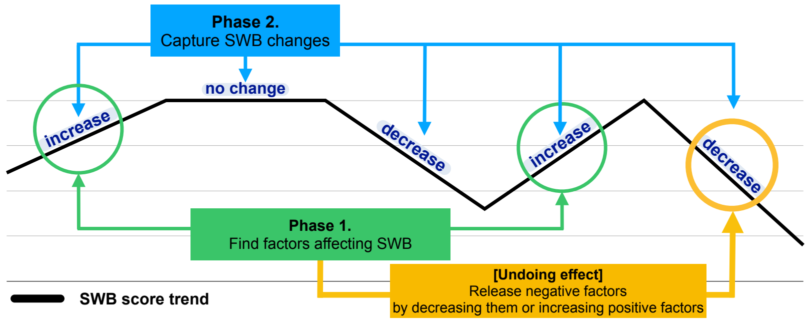

Figure 3: Supporting SWB through the analysis of factors of SWB (i.e., undoing effect).

5.3 Smartphone life features

As the smartphone is used in various parts of daily life, we can peek into a user's everyday life through such devices. We thus attempted to capture participants' daily lives from smartphone use as follows.

Smartphone app use: To associate smartphone behavior with real life, we categorized many apps, based on the Google Play Store categories, into 12 types – Entertainments&Music, Games&Comics, Social&Communication, Health&Wellness, Education, Shopping, Expense (general expenditure), ArtDesign&Photo, Food&Drink, Travel, News&Magazine, Others – that represent daily activities. We then calculated the rate of usage time for each category per day to see the impact of each app category on people's SWB. Note that we considered the top three app categories – Social&Communication, Entertainment&Music, Game&Comics – for analysis and modeling because we found a significant difference in use between those categories and others (i.e., the use amount of the apps in other categories is very low compared to that of the top three apps). We additionally considered the frequency of Expense and total app usage time.

Smartphone usage time: We calculated smartphone usage time via the ratio of total screen on/off time for three segments of the day (i.e., morning, afternoon, evening), which were found to be important factors discussed in prior research [45].

6 PHASES OF ANALYSIS

Our analysis of subjective well-being (SWB) consists of two phases.

6.1 Phase 1: Factors related to SWB

We investigated how smartphone-based features affect the overall SWB of individuals. SWB has been known as a highly subjective, complex concept that varies by individuals; thus, it is important to define and use features that affect SWB for a more accurate interpretation of it. Hence, we measured the factors that influence the increase and decrease in SWB. We used a hierarchical regression method to analyze the effect of a predictor variable after controlling for other variables. This "control" is achieved by calculating the change in the adjusted R^2 at each step of the analysis, thus accounting for the increment in variance after each variable (or group of variables) is entered into the regression model [40]. We explored the role of real life and smartphone life features on SWB by testing two different hierarchical regression models after controlling for other predictors of user attributes, including gender, SAS, five BFI features. Table 4 summarizes the results.

6.2 Phase 2: Classification of SWB changes

From the results in Phase 1, we were able to identify the factors that affect SWB. As previously mentioned, we applied a classification perspective to modeling in order to better capture a group of trends (i.e., increase, decrease, and no change) in SWB, which is useful to provide timely and appropriate feedback and articulate how undoing effects can play a role in balancing SWB. For end-users' perspective, providing feedback based on an individual classification result would be more straightforward than the one based on a regression result (i.e., SWB is highly influenced by individuals). To capture SWB changes, we developed a classification model with classic machine learning algorithms (e.g., decision tree, random forest) that were widely used by prior related studies (Table 1).

Our models were designed to classify three categories in the SWB score: increase, no change, and decrease. The ground truth labels were set to increase when the SWB score increased from the previous day, to no change when there was no change, and to decrease when the score decreased from the previous day. On average, the proportion of the increase, no change, and decreased classes was 42%, 15%, and 43%, respectively. For modeling, we used 80% of the data as the training set and the remaining 20% days as the test set. Regarding a model evaluation metric, we used a macro-average F1-score (or F1-macro score). In our analysis, F1-macro is preferred over F1-micro as the former gives equal importance to each class whereas the later gives equal importance to each sample. This means that, in F1-micro, the more the number of samples, the more say it has in the final score thus favoring majority classes (which is much like accuracy).

7 RESULTS

7.1 Phase 1: Factors on SWB

Table 4 summarizes the results of the hierarchical regression models. Model 1 shows the significance of the user demographic factors on SWB. Model 2 shows the factors affecting SWB while controlling for the user demographic information. Model 1 resulted in an adjusted R^2 value of 0.43 ($p < 0.01$). Model 2, which specifically focused on the factors of real life and those of smartphone life, resulted in the adjusted R^2 value of 0.49 ($p < 0.01$), a 6% increase of Model 1. This indicates that the user's demographic factors have a more significant impact on his/her SWB. Another insight is that adding additional real- and smartphone-life factors derived from passive smartphone sensor data helped increase model performance to

Type	Independent Variable	Model 1 β	Model 2 β
User	gender	0.09**	0.09**
	RSE (Resenberg's Self-Esteem)	0.32**	0.32**
	PPC (Positive Psychological Capital)	0.09**	0.08**
	PHQ (Patient Health Questionnaire)	-0.20**	-0.21**
	SAS (Smartphone Addiction Scale)	-0.02	-0.01
	Openness	0.03**	0.03**
	Conscientiousness	0.10**	0.11**
	Agreeableness	0.16**	0.16**
	Extraversion	0.05**	0.04**
	Neuroticism	-0.17**	-0.17**
Real life	Location change		0.01
	Time spent on campus		-0.07**
	Total sleep time		-0.02
	Ratio of stationary		-0.06**
Smartphone life	Expense (general expenditures)		-0.03**
	Social & Communication		-0.01
	Entertainment & Music		-0.03
	Game & Comics		-0.01
	App usage time		-0.04**
	Phone usage time (morning)		0.01
	Phone usage time (afternoon)		-0.02
	Phone usage time (evening)		-0.03**
Adjusted R^2		0.43**	0.49**

*p<0.05, **p<0.01

Table 4: Results of hierarchical regression. The dependent variable was the SWB value. We note the features that showed negative coefficients to SWB. This is because SWB could increase if those negative features are controlled. Model 2 considers the variables of real life and smartphone life while controlling for a user's inherent attributes.

some extent. The following are more specific insights from the models.

First, regarding the user factors, the male participants generally showed greater SWB than the female participants. Positive aspects of a user (i.e., RSE and PPC) showed positive associations with SWB. On the other hand, negative aspects (i.e., PHQ, SAS) of a user showed negative associations with SWB. These results align well with our expectations and prior studies [11, 12, 16, 26]. SAS did not show any significant influence. For personality, participants with greater openness, conscientiousness, agreeableness, and extraversion showed greater SWB, while those with neuroticism showed a negative association with SWB.

Second, regarding real life factors, spending more time on campus led to lower SWB. Some other factors (i.e., location change and total sleep time) did not show a strong influence on SWB. Unlike location change, the ratio of stationary activity (not moving) showed a negative association with SWB.

Third, for smartphone life factors, spending more money and using more apps are negatively associated with SWB. The use of social and communication apps did not show a strong influence on SWB. Using the smartphone more in the evening is negatively associated with SWB, while use in the morning and afternoon did not show a strong influence on SWB.

Depending on the results of the high degree of coefficients with p-value ($p < 0.05$) in the individual characteristics of the user characteristics (self-esteem, positive psychological capital, personality), we can see that SWB is highly influenced by individual tendencies and characteristics. This emphasizes that it will be more appropriate to reflect individual characteristics (rather than considering a group of users together) when establishing classification models for SWB change tracking.

7.2 Phase 2: Predicting the SWB changes

In Phase 2, we developed a classification model to capture the SWB changes based on high performance models from previous studies [8, 23, 53]. Up to 70% F1-macro score was found when individual models were built, and the average F1-macro score for all users was 38%. Considering the fact that SWB is highly influenced by individuals in the previous regression results, the average F1-macro result was somewhat low due to the differences in individual SWB distribution and those in individual characteristics.

Therefore, we compared users by dividing them into either a high (F1-macro score >= 50%) or a low group (F1-macro score < 50%) in order to see what characteristics cause the differences in the predictions of one's SWB changes. There was a significant difference in smartphone usage – app usage time (t(76)=3.30, p=0.001), Phone usage time of the morning (t(76)=4.62, p<0.001), afternoon (t(76)=4.35, p<0.001), and evening (t(76)=4.29, p<0.001) – when comparing data between the high and low groups. Additionally, when comparing their daily smartphone usage time, the high group users tend to spend more time using smartphones per day than the low group users. This suggests a feasibility of more reliably tracking SWB of active smartphone users than less active smartphone users.

8 DISCUSSION

SWB has a significant impact on individuals and society. SWB is fundamental to the overall health of individuals, enabling them to increase productivity, successfully overcome difficulties, and achieve life goals. SWB also makes social relationships, the community, and the society healthier and stronger. Technology can play an important role in increasing and maintaining SWB, and we focused thus on smartphone technology, which substantiates prior research efforts. Through the four-month user study with 78 participants, we examined how passive smartphone sensing data explains the levels and changes of SWB and what factors affect their variety.

8.1 Insights from Phase 1: Regression

In Phase 1, we found that the amount of smartphone use is generally negatively related to SWB. Since it is unrealistic not to use a smartphone in modern society, we looked at other elements that are strongly related to SWB.

First, we employed a hierarchical regression method in order to control a user's inherent attributes, because such a strong relationship has been identified in many prior studies. As we expected, the influence of user attributes was significant. Most variables showed significant associations with SWB and highly affected the model performance. This result highlights the importance of considering user characteristics in building a model for a subjective concept (e.g., SWB) for individuals. The result also suggests a necessity for building a personalized model. Given the sparsity of training data at the early stage of modeling, it is possible to start from a generalized model and then tailor it to individuals as more information is collected. Yet, from our finding, we want to emphasize that with the features of passive smartphone sensor data, we observed a 6% increase in the adjusted R^2 score, and that examining the influence of each feature and applying salient ones into modeling is important.

Second, while location change in itself did not show a significant effect on SWB, a high ratio of stationary activity showed a significantly negative effect. This indicates that periodically encouraging users to take a short walk, even if not necessarily visiting many places, would be helpful.

Third, we did not find a strong influence of any specific app category on SWB. However, when we considered the overall use time of all apps, the more time people spent using the apps, the lower SWB they had. We also captured the number of card transactions related to spending and found that greater spending led to less SWB. The relationship between spending money and well-being (or happiness) can vary depending on users and contexts, and research indicates understanding how the money is spent aids in its correlation with the individual [15, 36]. Since we only collected the numbers of transactions and not their types, applying type information to user modeling would be helpful.

Lastly, we found that greater use of a smartphone in the evening is associated with a decrease in SWB. Prior research reported that screen-on activities in the evening (6-9PM) are an important feature for detecting stress [45], which is quite well aligned with the findings in our study.

8.2 Insights from Phase 2: Classification

As we found great influence of individual factors on SWB, in Phase 2, we built the classification model for each participant. Although the F1-macro score of each model varied (which also complies with the regression result), it was confirmed that SWB could be tracked with up to 70% F1-macro score especially for active smartphone users. This further implies that feedback or intervention from the smartphone for SWB management could be useful for those users. Here we present some examples of providing suitable feedback tailored to an individual's smartphone use at the time of SWB decrease. We especially looked at the smartphone features that yielded significant difference between the case of SWB increase and that of SWB decrease.

$User_A$ (70% F1-macro score) showed a significant difference in using the Expense app and evening phone usage ($p<0.05$) between the increase and decrease (regarding SWB increase, $User_A$ showed more Expense and less phone use in the evening). With this result, encouraging (reasonable) expense or reducing phone use at the time of SWB decrease can be one possible way to improve SWB [28].

Another example is the use of SNS application. Both $User_B$ and $User_C$ showed significant differences in the use of SNS between SWB increase and SWB decrease; however, the patterns were different. $User_B$ showed less SNS use, while $User_C$ showed more SNS use, at the time of SWB increase. This result again highlights the need for providing feedback based on individual characteristics.

8.3 Limitations and future work

While many mental health studies have tried to find ways to support people's SWB through group comparison analysis, social psychology researchers emphasize that people tend to have their own preferences for happiness-boosting activities rather than following a regimented protocol [39]. This highlights the importance of self-strategy. In our study, we developed a model based on daily characteristics, focusing on individual changes to look into solutions to improve SWB by individuals through positive and timely intervention.

We acknowledge that the results of the model are not impressively high enough. Perhaps this is because of the insufficient number of SWB responses. However, it should be noted that the purpose of our study is not to identify highly accurate, in-the-moment SWB, but to investigate the feasibility of detecting SWB trends via passive smartphone sensing data that reflects one's behaviors. This justifies the EMA data collection request for the reflection on SWB applied in our study. Additionally, according to the studies related to SWB [14, 47], tracking trends of SWB requires a sufficient amount of time. Thus, our next step is to collect longer periods and more amount of data, build a more accurate and comprehensive model that understands the trends of SWB changes, and provide users with useful feedback.

Another limitation is the study participant. All participants in our study were university students who are in their 20s and show high smartphone use and great familiarity. Their life and smartphone use patterns may be quite different from populations of other demographics (e.g., older age groups). Our study participants were also skewed toward male students. Thus, our findings and insights may not be generalized. In our future work, we plan to run user studies with more diverse populations in age, gender, technical affinity, etc., and present a more comprehensive analysis of positive computing through smartphone use.

9 CONCLUSION

In modern society, many people are exhibiting great interest in and trying to improve their subjective well-being (SWB). This paper presents a study of modeling SWB and identifying salient factors on SWB from passive smartphone sensing, where people's *digital phenotypes* can be extracted from their smartphones. Our analysis is based on smartphone data collected from 78 college students over four months. Our regression analysis highlights the significance of user attributes on SWB (e.g., personality, self-esteem) and salient factors (e.g., time spent on campus, ratio of stationary activity, expenses, app/phone usage time) that significantly account for SWB. Our classification analysis shows the potential for detecting three types of SWB changes (i.e., increase, decrease, and no change) with a reasonable performance as well as for improving a model to be more tailored to an individual. We hope that our study findings and insights can be further investigated in terms of discovering features relevant to SWB and of improving SWB models, and be applied to realize digital well-being as part of positive computing research.

ACKNOWLEDGMENTS

This work was funded by National Research Foundation of Korea grant by Korea government (the Ministry of Science and ICT and the Institute for Information and Communications Technology Promotion): 2017M3C4A708353323, IITP-2020-2018-0-01431.

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