Journal of Aeronautics and Space Technologies

16(2) (2023) 1-19

Journal Homepage: jast.hho.msu.edu.tr

RESEARCH ARTICLE

Predicting Subjective Well-being from a Psychological Perspective

Psikolojik Bakış Açısıyla Öznel Sağlık Tahmini

Nail Şenbaş[1], S. Emre Alptekin[2*]

[1] *Galatasaray University, Department of Industrial Engineering, 34343 Istanbul, Türkiye*
[2] *Galatasaray University, Department of Industrial Engineering, 34343 Istanbul, Türkiye*

Received: *August 17, 2022* ***Revised:*** *February 14, 2023* ***Accepted:*** *June 22, 2023*

Abstract

Recent advances in pervasive computing enable the collection of personal health-related data using various sensors in daily life. Subjective well-being (SWB) considers how people experience and evaluate their lives and specific domains and activities in their lives. Human behavior modeling and analysis, particularly the quantification of SWB, is still challenging, as there are variations in its definition and measurement. Psychology literature defines different perspectives for SWB, such as hedonic, eudaimonic, or psychologic. In this paper, we propose a model for predicting an individual's SWB from a psychological perspective. We use the data of The NetHealth study, a heterogeneous data set of 577 student participants from the University of Notre Dame. It contains data about individuals' daily activities collected via smart wristbands, social relationships monitored through smartphones, and personality traits obtained from surveys. We develop a multi-class classifier based on commonly accepted machine learning algorithms. The results enable us to predict an individual's well-being almost with an accuracy of 80%. We show that such a pervasive application can be offered as a personalized well-being assistant.

Keywords: Subjective Well-Being (SWB), Psychology, Machine Learning, Personalized Well-Being Assistant.

Öz

Yaygın bilişim alanındaki son gelişmeler sayesinde, çeşitli sensörler kullanılarak günlük yaşamda kişisel sağlıkla ilgili veriler toplanabilmektedir. Öznel sağlık, insanların yaşamlarını ve yaşamlarındaki belirli alanları ve etkinlikleri nasıl deneyimlediklerini ve değerlendirdiklerini konu alır. İnsan davranışı modelleme ve analizi, özellikle öznel sağlığın sayısallaştırılması hala zorlu bir problemdir, çünkü öznel sağlığın tanımında ve ölçümünde farklılıklar bulunmaktadır. Psikoloji literatürü, öznel sağlık için hedonik, ödemonik veya psikolojik gibi farklı bakış açılarından bakar. Bu makalede, bir bireyin öznel sağlığına psikolojik bir perspektiften bakılmakta ve bunu tahmin etmek için bir model önerilmektedir. Notre Dame Üniversitesi'nden 577 öğrencinin katılıyla hazırlanan heterojen bir veri kümesi olan NetHealth verileri kullanılmaktadır. Bu veri kümesi içinde akıllı bileklikler aracılığıyla toplanan bireylerin günlük aktiviteleri, akıllı telefonlar aracılığıyla izlenen sosyal ilişkileri ve anketlerden elde edilen kişilik özellikleri bulunmaktadır. Yaygın olarak kabul gören makine öğrenme algoritmalarına dayalı çok sınıflı bir sınıflandırıcı geliştirilmiştir. Sonuçlar, bir bireyin öznel sağlık seviyesini yaklaşık %80 doğrulukla tahmin edebildiğimizi göstermiştir. Bu şekilde bir uygulamanın, kişiselleştirilmiş bir sağlık asistanı olarak sunulabileceği gösterilmiştir.

Anahtar Kelimeler: Öznel Sağlık, Psikoloji, Makine Öğrenmesi, Kişiselleştirilmiş Sağlık Asistanı.

*Corresponding Author
E-mail: ealptekin@gsu.edu.tr

1. INTRODUCTION

Well-being is a fact that concerns every person in society. It is desired to be improved and pursued at a reasonable level in every part of the life span. That is because people have higher expectations for a long and high-quality life. The interest in measuring well-being has exploded in recent years, guided by the demand for societal transformation with a contemporary vision for health that prioritizes well-being at the center [1].

In ancient history, well-being or "happiness" is a longstanding psychological terminology, and its complexity brings many definitions. In the scope of the science of happiness and well-being, Luhmann's research recounts the paradigm shifts that provide a review of past and current well-being theories, longitudinal empirical studies, and essential classifications for theoretical approaches [2]. The review article of Ed Diener brings the modern critical concepts of well-being with definitions together, such as subjective, psychological, hedonic, emotional, eudaimonic well-being, quality of life, etc. [3]. Among these concepts, subjective well-being (SWB) has shown considerable growth in the field with an exponential increase in scientific articles. SWB refers to the extent to which a person believes or feels that their life is going well and reflects an overall evaluation of the quality of a person's life from their perspective [3]. It is a subjective concept, and it is not synonymous with well-being. SWB can be considered one of the best conventional concepts of well-being, which may be used as an easily measurable fact for overall well-being.

The advancement of SWB has reformed from the various definition concepts to mainly validated measurement approaches over ten years [3, 4]. Technologies in well-being are utilized by smartphones, wearable devices, tangible devices, and social media platforms on the Internet. The examples are classified as medical and non-medical projects in tables [5]. Non-medical studies detect stress and measure mood, and emotional states to improve well-being [5, 6]. However, they commonly lack well-being measurement or validation. The weakest part is that they do not have any scientific examination and evaluation by comprehensive research [5, 6]. Medical studies made use of mental well-being to detect mainly depression and anxiety. They have prediction models with validated questionnaires for measurements, such as the Patient Health Questionnaire (PHQ-4, PHQ-8), and Quick Inventory of Depressive Symptomatology (QIDS) [6, 7]. Most of the existing studies on mental well-being have several limitations [6, 7]. Firstly, most are conducted on a limited number of individuals with a limited time. A limited number of individuals results in the lack of statistical power and personalization of studies. The limited short-term period cannot meet the data required for machine learning approaches. While machine learning improves itself for well-being estimation, it essentially requires a sizeable, labeled dataset to initially train the models, which can be challenging to obtain [6]. Secondly, focusing on a single type of data results in lower prediction accuracy due to the complexity [6, 7]. When continuous data is labeled with self-reports in the longitudinal timeline, the machine learning algorithms would be trained better and make predictions more accurately. However, this multi-type data approach depends on the high feedback ratios of the users' self-reports [6].

In order to go beyond the limitations of existing studies, the NetHealth Project data is used as the source of a machine learning model to predict subjective well-being [7]. Within the scope of SWB, two-component metrics are conceived: positive effects consisting of happiness and enjoyment and negative effects consisting of stress, depression, and sadness. Thus, not having depression or anxiety does not mean high SWB.

In this research, we first reviewed cutting-edge pervasive well-being technologies. We evaluated the tools and techniques in the literature regarding their effectiveness, capabilities, benefits, and drawbacks. Next, we explored the measurement of SWB in psychology literature. Finally, based on existing research, we determined the features of daily pervasive data that may serve to assess SWB. The main contribution of this paper is that it proposes a machine learning model for predicting a personally tailored SWB from a psychological perspective, using data obtained from smart wristbands, smartphones, and personality traits data from surveys.

The contributions of the study can be summarized as follows: Most of the studies in the related literature consider short-term (weeks or one month) datasets with few participants and few features. These conditions do not allow measuring subjective well-being. We provide a model comprising 4 years of data from multiple sources and from many participants. The feature selection process in the paper is based on psychological studies. The input and output of the model are designed to be meaningful in respect of those studies. Accordingly, the ground truth of subjective well-being is constructed. The model combines psychological surveys collected at the end of each term with daily collected passive data from smartphones and smartwatches. In this way, a subjective well-being prediction model is established that can be used widely in society without privacy concerns and requiring frequent responses.

The rest of the article is organized as follows: A detailed literature review is presented in Section 3, where the existing technologies and definitions are discovered, evaluated, and discussed. The proposed methodology is given in Section 4, together with the feature selection and data preparation processes. The technical performance of machine learning models is discussed in Section 5. In conclusion, the feasibility of the prediction model for SWB is shown, and the potential development for future work is discussed.

2. LITERATURE SURVEY

In this section, the works on well-being technologies are summarized. We intend to explore innovative interfaces to analyze existing and emerging technologies and how they are used to measure and improve well-being.

2.1. Technologies in Well-Being

In terms of assessing well-being, traditional methods work in the way of self-reporting; people recall their emotions and stresses in daily life, which are tracked in order to assist identify stressful factors [7] and use questionnaires such as the Positive and Negative Affect Schedule (PANAS) [8], Quick Inventory of Depressive Symptomatology (QIDS) [9] and the Patient Health Questionnaire (PHQ-9) [10], Satisfaction with Life Scale (SWLS) [11]. There are also validated ways to assess mental well-being in psychology and applied

by clinical visits [6]. However, the traditional way of assessing well-being by questionnaires is only available to apply in-clinic appointments. In this section, the state-of-the-art modern technological advancements for well-being are categorized, discussed, and evaluated.

2.1.1. Smartphones

The smartphone has various positions classified as active and passive data regarding users' interactions from different data sources. Active data is obtained from self-reports, application records, and changes or mood feedback from the users. Many applications have been developed to modernize and advance existing practices of recording mental well-being (such as Well Mind, Dayio, MoodPath, Calm, Headspace, etc.). Chatbot programs are designed to make individuals feel like they were talking with human beings [12], so the requirement to self-report is provided continually. Additionally, chatbots can mimic social human reactions in the conservations by advanced natural language algorithms. On the other hand, passive data is any available data gathered from the device records and sensors. The smartphone usage data is automatically taken from the device, so it does not require feedback or active recording. Therefore, it has a great variety of raw data types and gives opportunities for different detection purposes. Smartphone passive data can be used for monitoring emotion and stress by measuring speech analysis [5], mood state recognition (depression) by activity and mobility [13], the mood in bipolar disorder by usage patterns and application selection [14]; mood and well-being by frequency and duration of calls and SMS, email, web browsing, location [15], stress by sleep patterns and social contexts [16].

2.1.2. Wearable Devices

Due to the long-term usability and user-friendly interface, smartwatches and wrist-worn sensors are widely accepted in social life. They generally have non-invasive physiological sensors like GPS, accelerometer, heart rate sensor, and additional sensors in particular types. One of the main measures of stress is Galvanic Skin Response (GSR), which directly correlates with the sympathetic nervous system [17, 18, 19]. The other main measurement is Heart Rate Variability (HRV), which uses heartbeats changes to detect stress levels [6, 20]. By way of an accelerometer sensor, the intensity of physical activity is used to detect depression, which is assessed with Patient Health Questionnaire-9 (PHQ-9) [21].

2.1.3. Tangible Devices

Tangible devices are the interfaces that get digital information when users interact physically. For example, Emoball [6, 22] is a tangible device that will enable individuals to squeeze the ball, when they have feelings. The tangible device (ball) records their mood through the physical sensors. Mood sprite [23] is another example of a tangible device designed for patients to deal with anxiety, and stress and provide another way to feel relaxed.

2.1.4. Internet and Social Media Platforms

Recent studies have demonstrated increasing evidence that natural language processing can assess well-being through users' internet and social media posts. In this group, the keywords, and phrases in Twitter posts of users are processed for depression detection [5,24,25], and Facebook posts [5,26] for subjecting well-being [27]. Another popular alternative is using photos and videos from social media platforms to infer mental well-being [6]. The shared photos on Instagram may serve as well-being machine learning models to distinguish facial expressions relating to mental problems such as anxiety, depression, and more serious disorders like bipolar [28].

2.2. Evaluation of Technology in Well-Being

The big reason for the rising interest in well-being applications is their constant accessibility in individuals' life at any time. However, despite millions of users, there is not any scientific evidence supporting its use [6]. Their functionality is more focused on the practical approach of helping users improve their well-being when necessary than assessing well-being.

When the smartphone's active and passive data train machine learning models, they may predict emotions with a 70% accuracy [6]. Another essential research [29] proposed StressSense, providing a machine learning model to predict stress levels using human voice in social conversations. Another research states that the model detects daily stress levels with a 73% accuracy using the hybrid data model, such as Big Five Personality, social interactions like calls and messages, and weather conditions [29]. In [30] and [31], the authors state that individuals prefer physical (tangible) devices because they think the physical contact allows them to express their emotional experiences in a better way. In contrast, tangible devices lack continuous and rich data sets, an essential requirement for machine learning models. Furthermore, the studies on tangible devices are primarily on small scales, so they remain unproven, resulting in a lack of statistical analysis.

The hybrid models have multi-source data from smartphones and wearable devices using the same longitudinal timeline. These types of models have approximately 75% accuracy for stress detection by gathering continuous daily activities data and phone usage traits. The results show hybrid models have more efficient and higher accuracy than other single source models. Similarly, a wrist sensor, a mobile application, and self-reported PHQ-8 and PHQ-4 depression scores were used. The more physical sensors mean, the more accurate depression detection in the study results [32].

2.3. Well-Being in Psychology

Three main approaches to well-being are known in psychology literature. The evaluative approach defines well-being as the satisfaction of a person's life by self-evaluation and determination. The eudaimonic perspective focuses on whether individuals feel they have attained self-realization or are fully functioning or fulfilling a sense of purpose. The hedonic perspective determines the well-being regarding the degree of happiness or the frequency of experiences of pleasure and pain [1]. Ed Diener reported that "Subjective well-being reflects an overall evaluation of the quality of a person's life from their

perspective" [3]. According to [33], SWB has been associated with the hedonistic approach to well-being.

2.3.1. Subjective Well-Being

SWB is a highly active area of research [3]. SWB is a broad and general concept that includes the absence of mental illness and a higher level of life satisfaction and a better evaluation of individuals' lives [34]—the advancement of research on SWB guides scientists to understand the critical components of the concepts of well-being. In the light of these advancements, more knowledge about well-being allows applied studies to design many interfaces and models to improve the quality of persons in society [35].

2.3.2. Measurement of Subjective Well-Being

In the general overview of Ed Diener [3], one of the theories for SWB is concluded as: As the "top-down" and "bottom-up" theories of well-being are considered, "bottom-up" theories stated that well-being might be measured by summing up the positive and negative effects in respect of a person's evaluation. In this view, positive or "happy" events will increase an individual's well-being; in contrast, negative or "sad" events will decrease well-being [36]. Fordyce created a similar scale; "His question specifically mentions "happiness," and the response options list emotions varying from "elation" to "utter despair."." Based on the thoughtful engagement of the UK's Measuring National Well-Being Programme, the same four questions are widely used for existing well-being surveys [1]. In our study, similar questions would assess the individuals' SWB. The survey results would be labeled with the continuous passive data from hybrid interfaces. It is considered a hedonic well-being measurement. In Luhmann's research, it is suggested that most psychological theories relate to aspects of happiness and well-being that can be counted as components of SWB [2]. In Ed Diener's research, happiness is considered one of the significant feelings for SWB measurement [3]. Further, he has reported the core of SWB as "Can happiness be measured? And, if yes, in which way? An answer to this question is fundamental for an empirical science of subjective well-being" [37]. Thus, the happiness scale is used for SWB measurement in Diener research for new-well-being measurement in short and practical scales. "Lyubomirsky and Lepper's same four questions for the scale of happiness were also used in some studies, and it is the subjective happiness scale (SHS) as used in our study [38,39].

The study [45] applied similar approaches and techniques to the one in this paper. The models perform prediction of SWB by taking input texts of private messages, social media, and smartphone usage information. Labels for SWB values are both valid measures of satisfaction with life scale (SWLS) and WHO-5. SWLS is one of Deiner's surveys that aims to measure long-term overall well-being, and it is generally stable without changes in life circumstances, the same as the defined 'major event' in our dataset. On the other hand, WHO-5 is one of the proven assessments of mental well-being, especially depression over a short term (14 days). The similarity exists in the distribution of target SWB values in both SWLS and WHO-5 scales. The SWB labels are constructed binary and also trinary groups with different thresholds for the sake of high specificity as it is done in our study to have more balanced SWB classes.

Another work [46] implemented a model on a dataset that includes 'wild' data from smartwatches, smartphones, and applied questionnaires of 5400 days of 244 college students. The study gathered location, SMS, call, screen activities, the duration and frequency of sleep, bedtime, and sleep regularity. Questionnaires are applied twice a day and contain self-reports as stressed-calm, sad-happy, sick-healthy, and activity types.

2.3.3. The Validity of Measurement Scale

The short scales like SHS with 4-item or the scales of the UK's Measuring National Well-Being Programme would be helpful and applicable for larger populations [38]. The SHS is simple to use. Its brief form provides accurate assessment with low cost or respondent effort. [38]. However, only if the validity of scales exists, it is reasonable to apply the practical and short scales instead. The validity of the happiness scales as a measure of well-being and global mental health has been examined. The convergence with other happiness instruments allows to discriminate the different levels of happiness and prove that the happiness scale results correlate with commonly used mental health assessments [40]. This research showed that happiness measures are acceptable for well-being. However, the validity of any measurement is compulsory if it is desired to have reasonably meaningful in psychology desired. The SHS has a high correlation with other happiness and well-being measurements; furthermore, the construct theoretically and empirically [38]. Thus, the SHS scale has validity for the measurement of SWB, and it is used as the fundamental guideline to make an SWB output in this research.

3. PROPOSED MODEL

This work uses individuals' daily continuous data from smart wristbands, their social interactions tracked by smartphones, and personality traits data from surveys. Using them, a machine learning approach is developed to predict individualized subjective well-being. In terms of personalization, the model collects information on physical characteristics, personality traits (Big Five Inventory), confidence, and control using validated psychological surveys. The model is supported by daily continuous data from wearables such as physical activity, sleep duration, and heart rate patterns, as well as call duration and number of SMSs from smartphones. Finally, it is trained using subjective well-being assessments derived from self-report questionnaires completed on a regular basis. The main elements of the proposed model are illustrated in Figure 1.

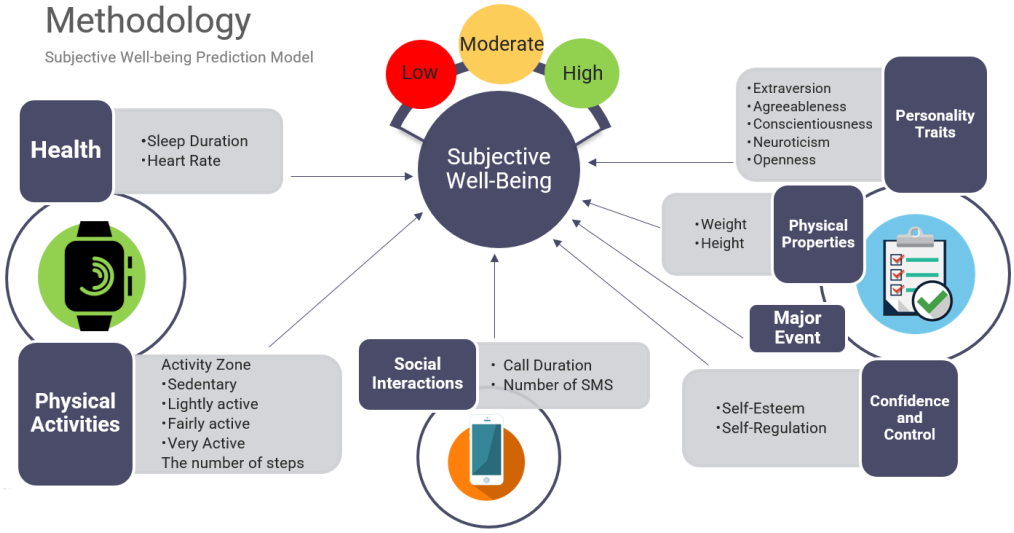


Figure 1. The machine learning model with the selected features.

4. METHODOLOGY

4.1. Dataset

We use the NetHealth Project's dataset. It is a multi-year longitudinal study of social networks and health. The study collected smartphone data, wearable sensor (Fitbit) data, and regular survey data (self-reports) from 577 undergraduate student participants from 2015 to 2019 [7, 16]. The multi-dimensionality and reliability of NetHealth data is the main reason for its selection as a source.

The NetHealth project includes a much longer timeline than the data from the existing related studies, so it may be considered more reliable [7]. NetHealth students were polled on their education programs, activity level, mental well-being, and sleep habits, as well as personal and family demographics. Social network data was collected from a smartphone application that records students' data obtained from calls and SMS [8]. Fitbit data would be summarized as physical activities (step counts, physical activity levels) and sleep habits (bedtime and sleep duration). The researchers apply periodic surveys that gather individuals' demographics, education, mental health, sleep quality, and personality traits [15]. SWB was measured annually in most studies, contrary to the SWB concept principles. The measurement of SWB is based on the detection of variation of SWB in the short term. Therefore, the SWB studies would be more efficient prediction models with higher accuracy, when the data gathering and applied surveys are more frequently done. However, longitudinal studies with short measurement periods to detect changes in well-being are very rare because of the high level of requirements [2].

4.2. Feature Selection

There are wide-range data available in the NetHealth study dataset. Therefore, the elimination of features is done among the different categories in NetHealth data regarding potential indicators of SWB. As a result, two categories of features are selected as continuous data features (Table 1) and survey data features (Table 2).

4.2.1. Personality Traits

The first principle is that the most known features about well-being in psychology literature are taken for the ground truth of SWB. Personality characteristics can be significant predictors of SWB. The most prominent connections with life happiness were between neuroticism and extraversion. The relationships between agreeableness and conscientiousness and particular well-being components were modest. However, they were smaller than neuroticism and extraversion [3]. Extroversion and neuroticism are the most consistently and strongly related to well-being [3]. Extraversion has been shown to predict positive effects, while neuroticism strongly indicates negative effects [35]. A widely accepted way to measure the personality traits of any individual is known Big Five Inventory (BFI). The BFI used in research is a validated scale to measure individuals' five personality traits: extraversion, agreeableness, openness, conscientiousness, and neuroticism. Individuals are asked to assess their level of agreement or disagreement with each statement [11]. Similar conclusions are shown in [11], which examined the robust findings that the BFI personality traits predict the satisfaction of life scales (SWLS) scores. BFI is also commonly used as an explanatory variable with other SWLS. Positive affect and negative affect have been consistently correlated with each of the BFI personality factors; however, extraversion has the highest degree of impact on determining positive affect, and neuroticism has a similar role for negative affect.

4.2.2. Confidence and Control

In [8], the authors reviewed the evidence that other traits, such as self-esteem and optimism are also moderately associated with SWB judgments. It is reported that self-esteem is a necessary emotional state with personality traits that affect SWB in the HUPPERT & SO and Deiner's models [9, 10]. In the NetHealth study, self-esteem is measured by the Rosenberg Self-Esteem Scale (RSES), defined in [10]. Furthermore, the self-esteem measured by RSES is considered one of the predictors for well-being and reported that low self-esteem was the best predictor of increases in sadness [41].

4.2.3. Social Interactions

The second principle is that the prepared data used in the model include the daily data of an individual. As much as possible, the continuous daily data would increase the model's performance. However, complex daily information would harm both the practicality and simplicity of the model. In the NetHealth study, many detailed categories of data are gathered from smartphones and FitBit devices daily, hourly, and even secondly. There should be a balance between these two opposite points. Another issue is the privacy of personal data. In NetHealth, all individuals' data is tagged as 'egoid', so they are anonymized in respect of individuals. The duration of calls and the number of SMSs (i-message, MMS, and WhatsApp) are taken from the smartphone data in communication. These two types of data would give a social interaction of individuals as input for the prediction model.

4.2.4. Physical Activities and Health

Physical activity and sleep duration are explicitly chosen to investigate the effects on mental well-being [42]. Sleep duration, heart rate, the activity time across four different groups (sedentary, lightly active, fairly active, and very active) are used in the model from the FitBit device data. Participants with higher step counts on weekend activities were happier, resulting

in having higher levels of SWB [8]. Given the correlations among these factors, we propose weekend activity be considered as a measure of informing one's SWB [8]. The number of steps can be used as an indicator of SWB. However, physical activities may change among individuals regarding mental or physical conditions. Intervention effects of exercise self-regulation on physical exercise are evaluated, and Exercise Self-Regulation Questionnaire (SRQ-E) is used for the evaluation [43]. When the questions of the SRQ-E survey are examined, it gives the purpose of individuals for physical activities, the attitudes towards them mentally, and their reaction to physical activities from SWB perspective. The weight and height of individuals are also added to the model to support the physical activity category of data from a physical condition perspective. In this manner, physical activity data would be a more meaningful and effective predictor for every individual by SRQ-E information.

4.2.5. Major Event

All the features examined above have reasonable effects on the SWB. The possible threats to the model have become more visible in the grand scheme of things, especially from life events. Individuals are bound by the "hedonic treadmill," which explains the process through which recent changes in living circumstances momentarily raise an individual's subjective standard before adapting to the current changes [35]. Studies on loss, marriage, and divorce show that more sophisticated theories of adaptability are viable. Research on SWB produces strong evidence that the individuals who had experienced major changes in their lives have significantly different SWB on average [2]. For example, individuals who experienced a divorce period tend to have lower SWB levels than married people [35]. Thus, life circumstances and experienced events also have significant effects on SWB in circumstances of stable personality and the level of SWB over time [3]. The solution for crucial "major event" threat to the model comes with a question in the surveys of the NetHealth study: "Have you experienced any major life changes in the past six months (e.g., loss of a loved one, a breakup, divorce, marriage)?".

Table 1. Continuous data features.

Features	Source	Unit
Call duration	Smartphone	Second
SMS		-
Heart rate	Smartwatch	-
Steps		-
Bedtime duration Sedentary Lightly active Fairly active Very active		Minute

Table 2. Survey data features.

Features	Scale	Range
Extraversion	Big Five Inventory	[1-5]
Agreeableness		
Conscientiousness		
Neuroticism		
Openness		
Self-esteem	Rosenberg Self-Esteem Scale	[0-50]
Self-regulation (SRQ)	Self-Regulation Questionnaire	[1-5]
External SRQE	Exercise Self-Regulation Questionnaire	[1-7]
Introjective SRQE		
Identified SRQE		
Intrinsic SRQE		
SRQE relative autonomy index		[(-12) - (+12)]
Weight	Pound	[90-270]
Height	Feet	[4.6-6.9]
Major event	Binary	0 or 1

4.3. Data Processing

Like every other dataset, the NetHealth data need to be cleaned before being processed (Figure 2). First, the BFI elements (self-esteem, and SQRE values) are measured in respect to their valid scales. Next, outliers, such as abnormal weight and heights, are eliminated. Finally, the major event is added to the model with a binary value.

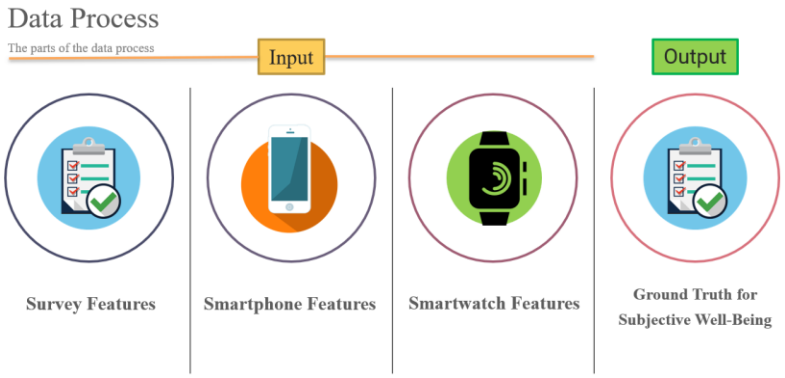


Figure 2. The data processing flow.

NetHealth project applied personality surveys at every wave, so we consider the personality characteristics, which were determined by Big Five Personality surveys in short time scales. However, BFI properties of individuals are updated by the new results of BFI from the next surveys in the waves. Hence, in theory, some participants' personalities might change over the three years. Thus, the Big Five Inventory blanks in the waves are completed with the last wave. Data for each wave in NetHealth is processed and fed into the model. The duration of calls, the number of SMSs, sedentary time, lightly active time, fairly active time, very active time, sleep duration, heart rate, and the number of steps are taken as a daily average between waves. The standard deviations of these features are also added to distinguish different distributions. Everyone has different survey dates in waves, so the average and standard deviations of features are calculated

and paired with each participant's survey dates for data consistency. For the accuracy of averages and standard deviation, the examples are selected in case they have %80 or higher compliance compared to the recent one.

The validity of the subjective happiness scale (SHS) shows that happiness is an essential measurement for SWB, so we use SHS for measuring SWB (Figure 3). To use SHS, the following answers are evaluated from the NetHealth surveys: the right of the statement to indicate how one generally feels (1-almost never, 4-almost always), "I am happy," and "I wish I could be as happy as others seem to be.". A new approach to assessing hedonic well-being taps emotional states without the overlay of evaluation. New approaches significantly reduce this problem by having individuals report relatively brief and recent periods [44]. To follow this advancement, the answers to the question "Taken all together, how would you say things are these days - would you say that you are thrilled, pretty happy, or not too happy?" is also prepared for the model. This addition makes the SWB measurement neither general feeling nor momentary evaluation. The SHS scores of individuals are divided into three levels of SWB groups as low, moderate, and high levels by approximately equal intervals. The classification thresholds are as follows:

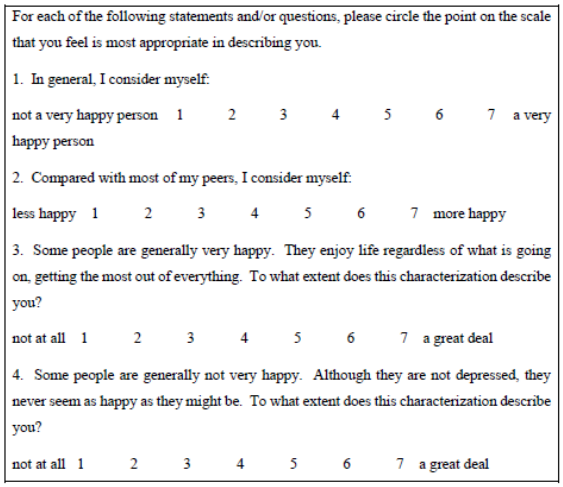
SHS score ≤ 7 as the low level of SWB (Observation: 65)
$7 <$ SHS score ≤ 10 as the moderate level of SWB (Observation: 448)
$10 <$ SHS score ≤ 15 as the high level of SWB (Observation: 64)

4.4. Machine Learning Models

The common machine learning algorithms are applied for classification. After the data processing, the input data and SWB scores of individuals as output data are paired. The sources of input data are mostly available and gather a huge amount of data, but the part of data with a low compliance rate (several FitBit data) or meaningless calls and messages (zero duration or length), etc. are eliminated. The SWB scores of participants are prepared from the surveys, which are applied every 3-4 months (every wave). Only if both input data and SWB scores of individuals are available at the same date periods, they are paired and used to train supervised machine learning models. After all, we had 577 samples, which is relatively low compared to the commonly used datasets for machine learning models. To overcome the drawbacks of a small dataset, widely used machine learning classifiers are applied using Scikit-Learn, Keras libraries in Python and MATLAB. Based on their high performances, we selected four of them (Boosted Trees, Quadratic Support Vector Machine, Cubic K-Nearest Neighbors, and Linear Discriminant Analysis).

By the rule of thumb, the normal size dataset is separated as 80% training subset and 20% validation, whereas in the large dataset, these ratios shift to 95% training subset and %5 for the validation one. However, our dataset was too small to separate into two subsets according to these rules of thumb. Additionally, two of the SWB levels have a relatively smaller number of samples. The validation set, which comes from separation, may not include the samples from each SWB level. The other common validation way is k-fold cross-validation. In this method, data is split into k folds. One of these folds is for testing and the rest (k-1) folds are for the training process. The machine learning model is trained with the k-1 training fold and the model's performance is measured by the one testing

fold. Then the validation result is calculated by taking the average of all performance measurements. Consequently, the validation of the model does not depend on only one test subset, and the performance is measured in respect of every fold of the dataset. Hence, when the dataset is small, the validation of the model would be more reliable and reasonable.


For each of the following statements and/or questions, please circle the point on the scale that you feel is most appropriate in describing you.

1. In general, I consider myself:

not a very happy person 1 2 3 4 5 6 7 a very happy person

2. Compared with most of my peers, I consider myself:

less happy 1 2 3 4 5 6 7 more happy

3. Some people are generally very happy. They enjoy life regardless of what is going on, getting the most out of everything. To what extent does this characterization describe you?

not at all 1 2 3 4 5 6 7 a great deal

4. Some people are generally not very happy. Although they are not depressed, they never seem as happy as they might be. To what extent does this characterization describe you?

not at all 1 2 3 4 5 6 7 a great deal

Figure 3. The subjective happiness scale.

5. RESULTS AND DISCUSSION

A neural network for classification is designed to predict the SWB classes of individuals. The structure of the proposed neural network consists of 7 fully connected layers, which has 1 input layer, 1 output layer, and 5 hidden layers. The input layer is created as a 33-dimensional feature set. The activation function of hidden layers is rectified linear activation function (ReLU). The output layer has 3 nodes, which use the sigmoid activation function to calculate the probability of belonging to each SWB level. The neural network is trained by Adam optimization algorithm with 0.00001 of learning rate concerning the classification loss function as categorical cross entropy. Due to the small number of samples, the dataset is split into training and test sets of 80% and 20%, respectively. To overcome the overfitting problem in the neural network model, the dropout function is applied in some of the hidden layers with ratios of 0.1 or 0.2. In the training process, the training set accuracy and validation set accuracy is balanced with dropout to avoid overfitting or bias in the neural network model. Consequently, the optimized neural network model achieves an accuracy of 80% in the training set and 75% in the validation set. The performances of the other used algorithms are compared in Table 3.

The top performance is achieved by the neural network with hyperparameter tune with 79.3% validation accuracy. However, it would be better to consider the area under curve (AUC) measurement, when evaluating classification models. AUC values indicate the separability skill of the model between SWB levels when making the prediction. The validation accuracies of the models are very close. However, the quadratic SVM has a

much higher capability of distinguishing proper predictions between classes, with 75.6% accuracy.

Table 3. Performances of machine learning models.

Model Type	Validation Accuracy	Area Under Curve (AUC)			F1 Macro	F1 Weighted
		Low	Moderate	High		
Neural Network With Hyperparameter Tune	79.3%	0.56	0.51	0.52	0.298	0.683
CUBIC KNN (K- Nearest Neighbours)	77.5%	0.55	0.50	0.49	0.320	0.687
LDA (Linear Discriminant Analysis)	76.4%	0.58	0.51	0.47	0.372	0.700
Quadratic SVM (Support Vector Machine)	75.6%	0.65	0.52	0.60	0.367	0.695

When F1 scores are used to measure the performance of the model, in this case, LDA method outperforms the quadratic SVM and LDA. Table 4 gives the details of confusion matrix calculations of the LDA method, as it is the best performing among the four methods.

Table 4. Confusion matrix of the LDA method.

True Class	Predicted Class			TP	FP	FN	Precision	Recall	F1 Scores	Weights
	0	1	2							
0	6	58	1	6	14	59	0.300	0.092	0.141	0.113
1	14	431	3	431	118	17	0.785	0.962	0.865	0.776
2	0	60	4	4	4	60	0.500	0.063	0.111	0.111

One of the related works [45] does not calculate AUC values for the classes, but F1 scores are available. F1 macro score of the best model starts from 0.381 like our work's result of LDA algorithm. F1 weighted scores of our work overwhelm by having 0.70. The best result of the trinary classification model is Ada-Boost model with the F1-weighted score of 0.493. In our paper, the proposed model focuses on SWB prediction in the medium term (approximately 3 months) between SWLS and WHO-5 by using the Subjective Happiness Scale, which is more related to daily life well-being than clinical diagnosis as depression. The long-term low SWB scores in the results may indicate depression, and it can be used as a preventive purpose.

The LDA model in another related work [46] reveals an accuracy of 58% and an F1 score of 0.65. The model uses a similar type of framework but has binary target labels. In [46], the machine learning model proposes giving recommendations to improve well-being by learning patterns of modifiable health behaviors, which are major factors in well-being.

6. CONCLUSION

SWB has a sphere of impact in all aspects of an individual's life. It indicates that even whether you have a mental (depression, anxiety, etc.) or a fatal physical illness. Our paper applies commonly used machine learning models for classification and provides a comparison of performances. We aim to demonstrate that a machine learning model can

predict an individual's well-being from a psychological perspective almost with an 80% accuracy by using data from her/his daily activities collected via smart wristbands, social relationships monitored by smartphones, and personality traits data from surveys.

The primary reason for the limited performance of the models would be the insufficient number of samples. The dataset is rich in many aspects; however, it needs more frequent data collection for SWB measurements as labeled data, which is required for supervised machine learning models. Another limitation due to the small-size dataset is the personalization of the prediction model. Sequential machine learning models cannot be used in the methodology. As the NetHealth study is applied to university students, the sample population consists of a specific age interval. Theoretically, this property of the dataset could be a limitation in terms of the generalization of the model. Practically, the proposed machine learning model could be used to develop a personalized well-being assistant via smartphone and wearable device data.

The work provides a model comprising 4 years of data from multiple sources and from many participants, which differentiates from the related works in the literature. Personality differences are one of the major obstacles to subjective well-being prediction. The proposed model has the potential to be personalized via online learning by providing feedback with passive data via smartphone and smartwatch.

For future research, the work can be extended with a larger dataset, including more frequently collected labeled data. The increased size of labeled data would allow applying complex machine learning models that explore data patterns in a time series.

REFERENCES

[1] T.J. VanderWeele, C. Trudel-Fitzgerald, P. Allin, C. Farrelly, G. Fletcher, D.E. Frederick, J. Hall, J.F. Helliwell, E.S. Kim, W.A. Lauinger, M.T. Lee, S. Lyubomirsky, S. Margolis, E. McNeely, N. Messer, L. Tay, V. Viswanath, D. Węziak-Białowolska, L.D. Kubzansky, *Current recommendations on the selection of measures for well-being,* Preventive Medicine **1**(33), 1-6 (2020).

[2] M. Luhmann, S. Intelisano, "Hedonic adaptation and the set point for subjective well-being," in *Handbook of well-being*, E. Diener, S. Oishi, L. Tay, Eds. Salt Lake City: DEF Publishers, 2018, pp. 219-243.

[3] E. Diener, R.E. Lucas, S. Oishi, *Advances and open questions in the science of subjective well-being,* Collabra: Psychology **4**(1), 1-49 (2018).

[4] W. Pavot, "The cornerstone of research on subjective well-being: Valid assessment methodology," in *Handbook of well-being*, E. Diener, S. Oishi, L. Tay, Eds. Salt Lake City: DEF Publishers, 2018, pp. 96-106.

[5] T. Glenn, S. Monteith, *New measures of mental state and behavior based on data collected from sensors, smartphones, and the Internet,* Current Psychiatry Reports **16**(12), 1-10 (2014).

[6] K. Woodward, E. Kanjo, D. Brown, T. McGinnity, B. Inkster, A. Tsanas, D. Macintyre, *Beyond mobile apps: A survey of technologies for mental well-being*, IEEE Transactions on Affective Computing **13**, 1216-1235 (2022).

[7] S. Liu, F. Vahedian, D.S. Hachen, O. Lizardo, C. Poellabauer, A. Striegel, T. Milenković, *Heterogeneous network approach to predict individuals' mental health,* ACM Transactions on Knowledge Discovery from Data **15**(2), 1-26 (2021).

[8] L. Faust, P. Jimenez, D. Hachen, O. Lizardo, A. Striegel, N. Chawla, "Long-term compliance habits: What early data tells us," *arxiv.org*, 2018. [Online]. Available: https://arxiv.org/abs/1804.04256. [Accessed: 19 July 2023].

[9] B. Gray-Little, V.S.L. Williams, T.D. Hancock, *An item response theory analysis of the Rosenberg Self-Esteem Scale,* Personality and Social Psychology Bulletin **23**(5), 443-451 (1997).

[10] L. Hone, J. Aaron, G. Schofield, S. Duncan, *Measuring flourishing: The impact of operational definitions on the prevalence of high levels of well-being,* International Journal of Wellbeing **4**(1), 62-90 (2014).

[11] R.T. Howell, M.L. Kern, S. Lyubomirsky, *Health benefits: Meta-analytically determining the impact of well-being on objective health outcomes,* Health Psychology Review **1**(1), 83–136 (2007).

[12] S. Abdul-Kade, J. Woods, *Survey on chatbot design techniques in speech conversation systems,* International Journal of Advanced Computer Science and Applications **6**(7), 72-80 (2015).

[13] A. Gruenerbl, V. Osmani, G. Bahle, J.C. Carrasco, S. Oehler, O. Mayora, C. Haring, P. Lukowicz, "Using smart phone mobility traces for the diagnosis of depressive and manic episodes in bipolar patients," in *Proc. of the 5th ACM International Conference of the Augmented Human, AH'14, 7-8 March 2014, Kobe, Japan* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/2582051.2582089. [Accessed: 19 July 2023].

[14] J. Alvarez-Lozano, M. Frost, V. Osmani, O. Mayora, M. Frost, J. Bardram, M.F. Jepsen, L.V. Kessing, "Tell me your apps and I will tell you your mood: correlation of apps usage with bipolar disorder state," in *Proc. of the ACM 7th International Conference on Pervasive Technologies Related to Assistive Environments, Petra'14, 27-30 May 2014, Rhodes, Greece* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/2674396.2674408. [Accessed: 19 July 2023].

[15] R. LiKamWa, Y. Liu, N.D. Lane, L. Zhong, "Can your smartphone infer your mood?," in *Proc. of the Second International Workshop on Sensing Applications on Mobile Phones, PhoneSense 2011*, *1 November 2011, Seattle, USA* [Online]. Available: CiteSeerX, https://citeseerx.ist.psu.edu/document?doi=bdb5a9a5d6c9b37193e0c2e9cb198f3edbccf6c2. [Accessed: 19 July 2023].

[16] D.C. Mohr, M. Zhang, S.M. Schueller, *Personal sensing: understanding mental health using ubiquitous sensors and machine learning,* Annual Review of Clinical Psychology **13**, 23-47 (2017).

[17] N. Sharma, T. Gedeon, *Objective measures, sensors and computational techniques for stress recognition and classification: A survey,* Computer Methods and Programs in Biomedicine **108**(3), 1287–1301 (2012).

[18] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Tröster, U. Ehlert, *Discriminating stress from cognitive load using a wearable EDA device,* IEEE Transactions on Information Technology in Biomedicine **14**(2), 410-417 (2010).

[19] F. Gravenhorst, A. Muaremi, G. Tröster, B. Arnrich, A. Gruenerbl, "Towards a mobile galvanic skin response measurement system for mentally disordered patients," in *Proc. of the 8th International Conference on Body Area Networks*, *BodyNets'13, 30 September - 2 October 2013, Boston, USA* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.4108/icst.bodynets.2013.253684. [Accessed: 19 July 2023].

[20] U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, C.M. Lim, J.S. Suri, *Heart rate variability: a review,* Medical and Biological Engineering and Computing **44**(12), 1031–1051 (2006).

[21] J.K. Vallance, E.A. Winkler, P.A. Gardiner, G.N. Healy, B.M. Lynch, N. Owen, *Associations of objectively-assessed physical activity and sedentary time with depression: NHANES(2005-2006),* Preventive Medicine **53**(4-5), 284-288 (2011).

[22] C. Fuentes, I. Rodríguez, V. Herskovic, "EmoBall: A Study on a Tangible Interface to Self-report Emotional Information Considering Digital Competences," in *Proc. of the 1st First International Conference of Ambient Intelligence for Health, AmIHEALTH 2015, Puerto Varas, Chile, 1-4 December, 2015*, J. Bravo, R. Hervás, V. Villareal, Eds. Switzerland: Springer, 2015. pp. 189–200.

[23] M. Barker, J. Linden, "Sprite Catcher: A Handheld Self-Reflection and Mindfulness Tool for Mental Healthcare," in *Proc. of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction, TEI'17, 20-23 March 2017, Yokohama, Japan* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/3024969.3025068. [Accessed: 19 July 2023].

[24] M. De Choudhury, M. Gamon, S. Counts, E. Horvitz, "Predicting depression via social media," in *Proc. of the 7th International AAAI Conference on Weblogs and Social Media, ICWSM 2013, 8-11 July 2013, Cambridge, USA* [Online]. Available: Association for the Advancement of Artificial Intelligence Library, https://ojs.aaai.org/index.php/ICWSM/article/view/14432. [Accessed: 19 July 2023].

[25] M. Nadeem, "Identifying Depression on Twitter," *arxiv.org*, 2016. [Online]. Available: https://arxiv.org/abs/1607.07384. [Accessed: 19 July 2023].

[26] A. Gruenerbl, V. Osmani, G. Bahle, J.C. Carrasco, S. Oehler, O. Mayora, C Haring, P. Lukowicz, "Using smart phone mobility traces for the diagnosis of depressive and manic episode in bipolar patients," in *Proc. of the 5th Augmented Human International Conference, AH'14, 7-8 March 2014, Kobe, Japan* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/2582051.2582089. [Accessed: 19 July 2023].

[27] P. Liu, W. Tov, M. Kosinski, D.J. Stillwell, L. Qiu, *Do Facebook status updates reflect subjective well-being?,* Cyberpsychology, Behavior, and Social Networking **18**(7), 373-379 (2015).

[28] L. Manikonda, M. De Choudhury, "Modeling and understanding visual attributes of mental health disclosures in social media," in *Proc. of the 2017 CHI Conference on*

Human Factors in Computing Systems, *CHI'17, 6-11 May 2017, Denver, USA* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/3025453.3025932. [Accessed: 19 July 2023].

[29] A. Bogomolov, B. Lepri, M. Ferron, F. Pianesi, A. Pentland, "Daily stress recognition from mobile phone data, weather conditions and individual traits," in *Proc. of the 22nd ACM international conference on Multimedia, MM'14, 3-7 November 2014, Orlando, USA* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/2647868.2654933. [Accessed: 19 July 2023].

[30] M. Matthews, G. Doherty, "In the mood: Engaging teenagers in psychotherapy using mobile phones," in *Proc. of the SIGCHI Conference on Human Factors in Computing Systems*, *CH'11, 7-12 May 2011, Vancouver, Canada* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/1978942.1979379. [Accessed: 19 July 2023].

[31] K. Niemantsverdriet, M. Versteeg, "Interactive Jewellery as Memory Cue: Designing a Sound Locket for Individual Reminiscence," in *Proc. of the 10th International Conference on Tangible, Embedded, and Embodied Interaction, TEI'16, 14-17 February 2016, Eindhoven, Netherlands* [Online]. Available: ACM Digital Library, https://dl.acm.org/doi/10.1145/2839462.2856524. [Accessed: 19 July 2023].

[32] K. Kroenke, R.L. Spitzer, J.B.W. Williams, B. Löwe, *An Ultra-Brief Screening Scale for Anxiety and Depression: The PHQ–4,* Psychosomatics **50**(6), 613–621 (2009).

[33] D. Kahneman, E. Diener, and N. Schwarz, *Well-Being: The Foundations of Hedonic Psychology*. New York: Russell Sage Foundation, 1999.

[34] A.M. Wood, S. Joseph, *The absence of positive psychological (eudemonic) well-being as a risk factor for depression: A ten year cohort study,* Journal of Affective Disorders **122**(3), 213–217 (2010).

[35] E. Diener, K. Ryan, *Subjective well-being: a general overview,* South African Journal of Psychology **39**(4), 391-406 (2009).

[36] E. Diener, *Assessing subjective well-being: Progress and opportunities,* Social Indicators Research **31**(2), 103-157 (1994).

[37] M. Eid, and R.J. Larsen, *The science of subjective well-being*. New York: Guilford Press, 2008.

[38] S. Lyubomirsky, H.S. Lepper, *A measure of subjective happiness: Preliminary reliability and construct validation,* Social Indicators Research **46**, 137-155 (1999).

[39] E. Diener, D. Wirtz, W. Tov, C. Kim-Prieto, D. Choi, S. Oishi, R. Biswas-Diener, *New well-being measures: Short scales to assess flourishing and positive and negative feelings,* Social Indicators Research **97**(2), 143-156 (2010).

[40] M.W. Fordyce, *A review of research on the happiness measures: A sixty-second index of happiness and mental health,* Social Indicators Research **20**(4), 355-381 (1988).

[41] J. Ciarrochi, P.C.L. Heaven, D. Fiona, *The impact of hope, self-esteem, and attributional style on adolescents' school grades and emotional well-being: A longitudinal study,* Journal of Research in Personality **41**(6), 1161-1178 (2007).

[42] P. Neha, D. Gothe, K. Ehlers, E.A. Salerno, J. Fanning, A.F. Kramer, E. McAuley, *Physical activity, sleep and quality of life in older adults: influence of physical, mental and*

social well-being, behavioral sleep medicine, Behavioral Sleep Medicine **18**(6), 797-808 (2019).

[43] L. Fleig, S. Lippke, S. Pomp, R. Schwarzer, *Intervention effects of exercise self-regulation on physical exercise and eating fruits and vegetables: a longitudinal study in orthopedic and cardiac rehabilitation,* Preventive Medicine **53**(3), 182-189 (2011).

[44] A. Steptoe, A. Deaton, A.A. Stone, *Subjective well-being, health, and aging,* The Lancet, **385**(9968), 640–648 (2015).

[45] P. Panicheva, L. Mararitsa, S. Sorokin, O. Koltsova, P. Rosso, *Predicting subjective well-being in a high-risk sample of Russian mental health app users,* EPJ Data Science **11**(1), 1-43 (2022).

[46] N. Ehimwenma, R. Picard, *Toward Assessing and Recommending Combinations of Behaviors for Improving Health and Well-Being,* ACM Transactions on Computing for Healthcare **1**(1), 1-29 (2020).

To Cite This Article: N. Şenbaş, S.E. Alptekin, Predicting Subjective Well-being from a Psychological Perspective, Journal of Aeronautics and Space Technologies 16(2), 1-19 (2023).

VITAE

Nail ŞENBAŞ received his B.Sc. degree in Civil Engineering from Boğaziçi University, in 2015. He received his M.Sc. degree in Industrial Engineering from Galatasaray University in 2017. He is currently working as Teaching Assistant at Contemporary Technology University in the USA.

S. Emre ALPTEKİN received his B.Sc. degree in Industrial Engineering in 1999 from Istanbul Technical University, his M.Sc. and Ph.D. degrees in Industrial Engineering from Galatasaray University in 2001 and 2006, respectively. He is currently an associate professor in Galatasaray University. His research interests machine learning applications, new product development, and decision support systems.