MATHEWS JOURNAL OF PSYCHIATRY & MENTAL HEALTH

Research Article

ISSN: 2474-7564

Vol No: 4, Issue: 1

Received Date: Mar 06 2019

Published Date: Apr 30 2019

Prediction of Adolescent Subjective Well-Being: A Machine Learning Approach

Z Naixin[1,3], L Chuanxin[2], A Lin[1,3], C Zhixuan[1,3], R Decheng[1,3], Y Fan[1,3], Y Ruixue[1,3], J Lei [1,3], B Yan[1,3], G Zhenming[1,3], M Gaini[1,3], X Fei[1,3], Y Fengping[1,3], Z Liping[5], R Gabriel[6], X Yifeng[3], H Lin[1,3], B Bo[4]*, H Guang[1,3]*, Y Tao[1,2,3]*

[1]Bio-X Institutes, Key Laboratory for the Genetics of Developmental and Neuropsychiatric Disorders, Shanghai Jiao Tong University, Shanghai, China

[2]School of Mental Health, Jining Medical University, Jining, Shandong, China

[3]Shanghai Key Laboratory of Psychotic Disorders, and Brain Science and Technology Research Center Shanghai Jiao Tong University, Shanghai, China

[4]Institute of Neurobiology, Jining Medical University, Jining, Shandong, China

[5]Shanghai Center for Women and Children's Health, Shanghai, China

[6]Department of psychiatry, EA4712 Behavior and Basal Ganglia Unit, Medical University of Rennes, 1 Rennes, France.

Corresponding Author:

Guang He*

Bio-X Center, Shanghai Jiao Tong University, 1954 Huashan Road, Shanghai 200030, P.R. China

ABSTRACT

Background and Objectives: Subjective well-being (SWB), also known as happiness, plays an important role in evaluating both mental and physical health. Adolescents deserve specific attention because they are under a great variety of stresses andare at-risk for mental disorders during adulthood.

Methods: We used Gradient Boosting Classifier, an innovative yet validated machine learning approach to analyze data from 10 518 Chinese adolescents. Online survey included 298 factors such as depression and personality. Quality control procedure was used to minimize biases due to online survey reports. We applied feature selection to achieve the balance between optimal prediction and result interpretation.

Results: Top 20 happiness risks and protective factors were finally brought intothe predicting model. About 90% individuals' SWB can be predicted correctly, the sensitivity and specificity were about 92% and 90% respectively.

Conclusions: This result identifies at-risk individuals according to new characteristics and established the foundation for adolescent prevention strategies.

Keywords: Prediction; Adolescent; Subjective Well-Being; Machine Learning

INTRODUCTION

Happy people tend to live longer and have better physical and mental health. Adolescence is a critical period since some results suggest that positive youth development can improve long-term health [1]. Furthermore, adolescent depression was a strong predictor of mental disorders during adulthood [2]. For example, many investigators had reported that undergraduate students suffered from depression and are vulnerable to suicide attempt and completed suicide [3-8]. In a meta-analysis, Ibrahim also concluded that undergraduate students were more prone to depression with high prevalence [9]. Therefore, robust identification of unhappy students is critical to develop and apply specific interventions to at-risk individuals. So far, traditional approaches adopted single self-report scale such as Centre for Epidemiologic Studies Depression Scale (CES-D), Satisfaction with Life Scale (SWL), and Positive and Negative Affect Schedule (PANAS) which are not reliable since SWB was multi-faceted [10]. Indeed, SWB contains many dimensions such as life-satisfaction, positive emotion, and negative emotion [11]. For these

DOI: https://doi.org/10.30654/MJPMH.10021

reasons, identifying unhappy students required multivariate approaches to adequately circumscribe the multifaceted construct of SWB.

As a multivariable big-data problem [12], machine learning can provide SWB problem with solutions that would outperform classical method. As such, previous studies had applied machine learning approaches to predict SWB. For example, Bogomolov used machine learning to predict SWB by using real-world and on-line data from mobile phone [13]. Saputri adopted the same method to predict country SWB [14,15] and Jatupaiboon used electroencephalogram to train model [16]. These studies showed that machine learning could predict SWB better than single scale measurement. However, these previous studies focused on adult population and their application in terms of preventive strategies toward mental health was limited. Moreover, recent learning approaches, such as ensemble methods, had shown improved classification accuracies.

Ensemble methods had been widely adopted recently because of its good performance. The general idea of "ensemble methods" was essentially based on constructing a set of simple classifiers and combining them. Final decisions were given by weighted or unweighted votes from each simple classifier, which contributes to model accuracy [17]. One of the most representative ensemble methods was gradient boosting algorithm. It combined a set of simple classifiers. Each of them performed on data with one distribution. Those weak classifiers generated one strong classifier which can achieve higher accuracy than other simple ones [18]. Finally, their performance would be improved. Gradient boosting algorithm had many advantages. First, it was insensitive to data with non-normal distributions and outliers. Additionally, we did not have any priori hypotheses about input variables, which should be considered by the boosting algorithm. This algorithm was also robust against the addition of irrelevant input variables due to trees' attribute [19].

Including both psychological and physiological parameters, we can take advantages of the gradient boosting algorithm to predict undergraduates' SWB with satisfying accuracy.

METHODS

Data collecting

All participants came from Jining Medical University.

Students (freshmen) who were entranced in 2016 and 2017 were recruited in this study in their first year. And students (sophomores) who were entranced in 2016 also took online survey in 2017 in their second year. We recruited 10 518 survey data in total. To minimize environmental influences, students were gathered and asked to complete the online scale together.

Online survey design

Scores of Satisfaction with Life Scale(SWL), Positive and Negative Affect Scale(PANAS) were used to measure undergraduate SWB. Other measurement items were summarized in Table1. Scales consisted of Adolescent Self-Rating Life Events Check List (ASLEC), Big Five Inventory (BFI), Child and Adolescent Social Support Scale(CASSS), Center for Epidemiologic Studies Depression Scale (CESD), Dispositional Flow Scale (DFS), General Self-Efficacy Scale (GSES), Utrecht Work Engagement Scale-Student (UWES-S) and Multidimensional-Multiattributional Causality Scale (MMCS). We also collected general information such as gender, blood type, exercise, sleep, religious, economical situations, parents' education level and characters. Moreover, four feedback questions and time elapsingwere designed for sifting reliable data.

Data processing

First, we dropped samples with 1 score feedback question, such as 'this survey is meaningless', 'harry when answering questions', 'hard to understand this questionnaire', and 'answers don't reflect truth'. In addition, only answering time within 99% confidence interval were included. Second, the data size was reduced to 10 272 in total. Then, dummy features (as Table1 shows) were encoded to one-hot codes and binary classifying features were encoded to 0/1 codes, which was the proper format for machine learning. Third, standardization was adopted to eliminate different orders' problem. After principal component analysis of SWL and PNANS, the foremost 2 components were calculated as 'pca' score. Whole data were divided into two datasets according to freshmen and sophomore. Data1 contained all freshmen's information (N=6 886), and data2 contained all sophomores' information (N=3 386). Top 30% samples with 'pca' were labeled as 1(data1: N=2062; data2: N=1016), bottom 30% were labeled as 0 (data1: N=2063; data2: N=1016). Remained 40% data were excluded in this study. After random shuffle, each dataset was divided into training set and testing set with a conventional ratio 7 (data1: N=2 887; data2: N=1422) to 3 (data1: N=1 238; data2: N=610).

DOI: https://doi.org/10.30654/MJPMH.10021

Table 1: Online scale items.

Column1	Description	Measurement
ASLEC	Adolescent negative life events	0(very low) to 130(very high)
BFI	Five personalities	Openness, Agreeableness, Conscientiousness, Neuroticism, Extraversion
CASSS	Social support	17(very low) to 85(very high)
CESD	Total score of CES-D	0(very low) to 60(very high)
DFS	Total score of 9 dimensions of DFS	9(very low) to 45(very high)
GSES	Total score of GSES	31(very low) to 155(very high)
PA	Total score of PANAS negative items	10(very low) to 50(very high)
NA	Total score of PANAS positive items	10(very low) to 50(very high)
SWL	Total score of SWLS	5(very low) to 35(very high)
UWESS	Total score of UWES-S	0(very low) to 102(very high)
MMCS	Total score of MMCS	1(totally disagree) to 5(totally agree)
gender	Gender	1(male), 0(female)
<u>BP</u>	Blood types	1(A type), 2(B type), 3(AB type),4(O type), 5(Don't know),
exercise	Average exercise time (min/per day)	1(0-30), 2(30-60), 3(60-120), 4(120+)
sleep	Sleep quality	1(very bad), 2(bad), 3(normal), 4(good), 5(very good)
weight	Weight	Measured by kilogram(kg)
height	Height	Measured by centimeter(cm)
<u>M.character</u>	Mather's character	1(serious), 2(optimistic), 3(gender),4(crude), 5(taciturn)
<u>F.character</u>	Father's character	1(serious), 2(optimistic), 3(gender),4(crude), 6(taciturn)
M.edu	Mother's education level	1(high) to 5(low)
F.edu	Father's education level	1(high) to 5(low)
Family¥	Family economic situation	1(low), 2(middle), 3(high)
Living¥	Average living expenses (¥/per month)	1(0-500), 2(500-1000), 3(1000-1500),4(1500-2000), 5(2000+)
minority	Han population or not	1(yes), 0(no)
register	Urban or Country	1(Urban), 0(Country)
<u>SP</u>	Political status	1(Chinese communist party), 2(Democratic party), 3(No party), 4(League member), 5(Public)
child	Singleton or Not	1(singleton), 0(not)
religious	Do you believe in religion	1(yes), 0(no)
feedback	Feedback on this testing	1(meaningless) to 5(meaningful)
time_elapsed	Online scale finishing time	Measured by seconds(s)

underlined items were one-hot coded dummy features

Feature selection

Each item of every scale was input as a feature, we included 298 features in total. In order to avoid over-fitting and facilitate practical application,, fewer features would be better. We assessed all 298 features simultaneously with elastic net regularization, which can avoid correlated factors over-fitting. This method would remove uninformative features and assign low weight to correlated ones. We selected the best 20 features from data1 and data2 separately. Further model construction would only consider these 20 features. This number was selected to balance prediction accuracy and usability in practical analysis. We also assessed models with 10 or 30 features.

Machine Learning Algorithm

This research applied computational language python and GradientBoostingClassifier (GBC) in scikit-learn (sklearn, http://scikit-learn.org/stable/index.html), a machine learning module in python, to build our predicting model. It was the model parameters which constructed one specific model. As an ensemble method, GradientBoostingClassifier combined multiple weak classifiers to produce more accurate prediction significantly, it was much better than any base classifiers. Initially, one specific classifier fit data. The next new classifier would re-weighted parameters to the direction of gradient descend, which would minimize loss function. Finally, a model with the minimum error on training data (70% dataset) was

DOI: https://doi.org/10.30654/MJPMH.10021

generated. Model performance was evaluated by confusion matrix, receiver operating curve (ROC), and area under curve (AUC). Considering different life patterns between freshmen and sophomores, two models on data1 (GBC1) and data2 (GBC2) were built separately.

Tuning parameters

To achieve better predicting accuracy, tuning hyper parameters of model was necessary. For example, model accuracy with different settings of two main important hyper parameters n_estimators and learning_rate has a typical pattern the model accuracy under different settings has typical patterns, including two main important hyper parameters n_estimators and learning_rate (as Figure1 shows). Each curve represented one classifier with a specific learning_rate. X-axis was n_estimators while y-axis was correct classification rate. Figure1 showed that classifier with appropriate n_estimators and learning_rate can reach the best accuracy. With many important hyper parameters (eg: max_depth, min_samples_split, min_samples_leaf, max_features) and trade-off problem, specific algorithm makes this process efficiently. A machine learning algorithm named GridSearchCV was applied to process optimal hyper parameters searching in GBC.

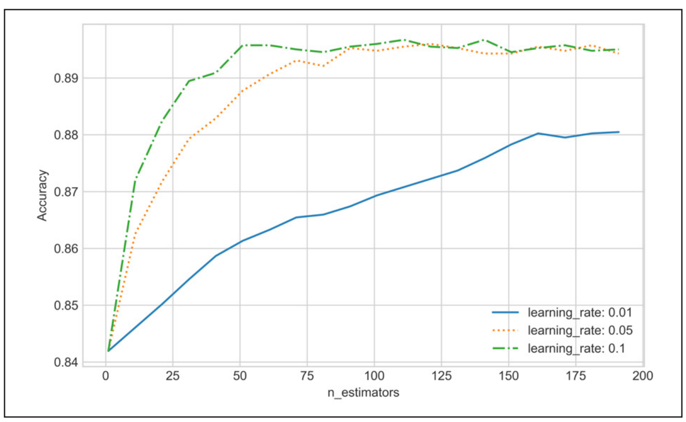

Figure 1: Typical pattern between n_estimators and learning_rate.

RESULTS

Label construction

Subjective well-being included three dimensions: life satisfaction, positive affect, and negative affect [20,21]. We took SWL score and PANAS two sub score (positive and negative affect score) as SWB measurement. After principal component analysis, we took foremost two components which can explain freshmen 82.5%(86.0%, sophomores) variance as 'pca' score for further label tagging. The 'pca' score was negative related with happiness, and it was calculated by formula listed below. Top 30% points were 1.87(2.69, sophomores) and bottom 30% points were -2.48(-2.47, sophomores). Observations with score higher than 1.87(2.69, sophomores) were labelled as unhappy while individuals with score lower than -2.48(-2.47, sophomores) were considered as happy.

Freshmen: 'pca' = 0.536*component1 + 0.289*component2

Sophomores: 'pca' = 0.509*component1 + 0.352*component2

Model Performance

After tuning parameters, GBC1 with 0.06 learning_rate enables model achieved best performance. GBC2 with default parameters was the best. Figure 2 showed models' ROCs. GBC had tiny advantage on predicting sophomores' SWB. Table 2 showed various model performance measurements on different sets of feature numbers. Models with 10, 20, and 30 predictors had no significantly difference.

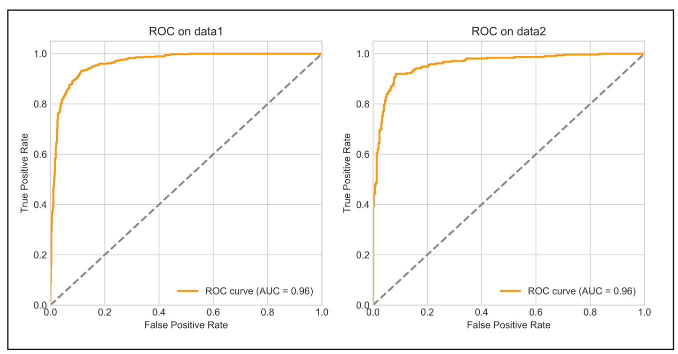

Figure 2: ROAUC.

Table 2 Model Evaluation.

	GBC1				GBC2			
	10 features	20 features	30 features	P-Value	10 features	20 features	30 features	P-Value
Accuracy	89.74%	90.47%	90.79%	0.23	89.02%	90.98%	91.15%	0.45
AUC	0.9564	0.9644	0.9042	0.58	0.9558	0.9596	0.9588	0.64
Sensitivity	90.85%	92.06%	92.57%	0.24	88.14%	91.99%	90.71%	0.7
Specificity	88.77%	89.07%	89.23%	0.2	89.93%	89.93%	91.61%	0.5
PPV	87.67%	88.10%	88.30%	0.22	90.16%	90.54%	91.88%	0.33
NPV	91.69%	92.73%	93.19%	0.24	87.87%	91.47%	90.40%	0.68

DOI: https://doi.org/10.30654/MJPMH.10021

ROC: receiver operating characteristic curve; AUC: area under curve.

Table 2 Model Evaluation.

AUC: area under receiver operating characteristic curve

PPV: positive predictive value

NPV: negative predictive value

Feature importance

All 20 selected features' relative importance for predicting undergraduate SWB were shown in Figure 3. Risk and protective factors with huge difference patterns can be observed between freshmen and sophomores. The top three predictors of freshmen were 'I felt fearful.' (CESD), 'Get nervous easily.' (BFI), 'I was bothered by things that usually don't bother me.' (CESD). The top three predictors of sophomores were questions of CESD: 'I was happy.', 'I felt fearful.', 'I felt that I could not shake off the blues even with help from my family or friends.'.

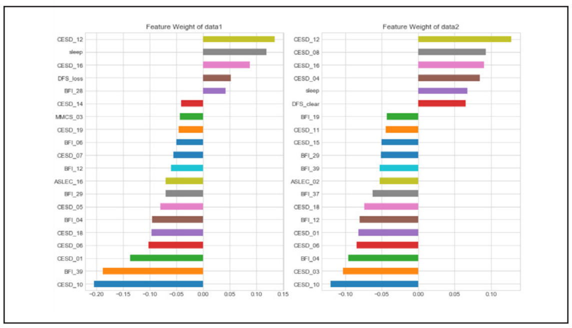

Figure 3: Top 20 features for predicting undergraduates' SWB.

CESD: Items of CES-D; sleep: self-reported sleep quantity; DFS_loss: one of nine dimensions of DFI, loss of self-consciousness; BFI: Items of BFI; MMCS: Items of MMCS; ASLEC: Items of ASLEC; DFS_clear: one of nine dimensions of DFI, clear goals

DISCUSSION

This paper presented a machine learning method, Gradient Boosting Classifier (GBC), to predict undergraduate subjective well-being (SWB). Two models were built on freshmen data (GBC1) and sophomore data (GBC2). The prediction accuracy achieved 90.47% (GBC1) and 90.98% (GBC2). Different SWB patterns between freshmen and sophomore were explored according to different important predictors. As we can know, this work might be the first one adopting machine learning method to predict adolescent happiness in Chinese population. Besides, two possible 20-items questionnaires for interpreting were generated (shown in Table3). Rather than evaluate happiness with redundant factors, these 20 self-reported questions may diagnose SWB more efficiently. Students with this simple self-test can monitor their mental health,and psychological consultation teachers could identify at-risk individuals easily by evaluating the scores of each question. For example, a depressive student with relative low sleep situation may receive sleep therapy.

Freshmen and sophomores shared 11 predictors. Most of those items measuring depressive symptoms were also important predictors. For both freshmen and sophomores, half predictors came from CESD. Depression and happiness

Table 3: 20 features of predicting undergraduate SWB.

Freshmen	Feature Description	Sophomore	Feature Description2
CESD_10	I felt fearful.	CESD_12	I was happy
BFI_39	Gets nervous easily.	CESD_10	I felt fearful
CESD_01	I was bothered by things that usually don't bother me.	CESD_03	I felt that I could not shake off the blues even with help from my family or friends
CESD_12	I was happy.	BFI_04	Is depressed, blue.
sleep	sleep quantity.	CESD_08	I felt hopeful about the future.
CESD_06	I felt depressed.	CESD_16	I enjoyed life.
CESD_18	I felt sad.	CESD_04	I felt that I was just as good as other people.
BFI_04	Is depressed, blue.	CESD_06	I felt depressed
CESD_16	I enjoyed life.	CESD_01	I was bothered by things that usually don't bother me.
CESD_05	I had trouble keeping my mind on what I was doing.	BFI_12	Starts quarrels with others.
BFI_29	Can be moody.	CESD_18	I felt sad.
ASLEC_16	Family financial difficulties.	sleep	sleep quantity
BFI_12	Starts quarrels with others.	DFS_clear	I know what I want to achieve.
			I clearly know what I want to do.
			My goals are clearly defined.
			I have a strong sense of what I want to accomplish.

DOI: https://doi.org/10.30654/MJPMH.10021

CESD_07	I felt that everything I did was as effort.	BFI_37	Is sometimes rude to others.
DFS_loss	I am not concerned with how I present myself.	ASLEC_02	Get the cold shoulder of discrimination.
	I am not worried about what others might be thinking of me.		
	I am not concerned with how others might be evaluating me.		
BFI_06	Is reserved.	BFI_39	Gets nervous easily.
CESD_19	I felt that people dislike me.	BFI_29	Can be moody.
MMCS_03	If I get low marks, I doubt my academic ability.	CESD_15	People were unfriendly.
BFI_28	Perseveres until the task is finished.	CESD_11	My sleep was restless.
CESD_14	I felt lonely.	BFI_19	Worries a lot.

Items are listed as predicting importance order. Shared factors are in bold. DFS_clear: clear goals; DFS_loss: loss of self-consciousness

are "mirror images", relationship between depression and SWB had already been reported [22,23]. Reasonably, happier students had less depressed. Since depression had been proved to be related to genomic background [24], the relationship between SWB and depression suggested that the possibility of 'biological happiness' in addition to 'sociological happiness'. A quantified SWB level could be possible in the future. Besides, a GWAS study had reported that parts of "SWB" SNPs are significantly associated with depression symptoms [25]. Both SWB and depression may be share some same genetic factors. Clinically, well-being therapy (WBT) was a psychotherapeutic strategy. It aimed to increase patients' mental health, and guide themselves to a state of positive emotion by emphasizing on self-observations. WBT has been proved as a successful way in easing depression [26]. Those results indicated a close relationship between happiness and depression, which may contribute to anti-depression therapy in the future.

Importance of personality questions were about the same as depressive items. Many studies had reported the strong relationship between personality and happiness [20,27]. In this study, consistent with previous studies, agreeableness, openness, conscientiousness and extraversion were positively correlated with happiness while neuroticism was negative related to happiness,. Since people with agreeableness, openness, conscientiousness and extraversion were more likely to get involved in positive social network. Those traits would contribute to positive enjoyment or life satisfaction as well. Happiness level of people with those personalities can increase at the same time. On the contrary, people with neuroticism tended to suffer more misfortunate feelings, which resulted in less joy or pleasures [28].

Two dimensions of DFS: loss of self-consciousness and clear goals, can affect undergraduates' SWB slightly. DFS was designed as measurement of flow. "Flow" was first put forward as an intrinsically optimal stated that result from intense engagement with daily activities [29]. In other words, people who were facing certain challengeable activities with matched skills would generate positive emotions during acting. Being intrinsically motivated, everyone can gain happiness because of a sense of euphoria and satisfaction [30]. We supposed college students can achieve SWB if they can be guided to experience more flow state.

Some limitations were worth noting. First, all participants came from the same college, which may not represent undergraduate population perfectly. In the future, we would try to seek for global cooperation to understand happiness predictors generally. And no validation studies had been conducted on our 20-items questionnaires which may possible be used to measure undergraduate SWB. The reliability and effectiveness needed to be further studied..

In conclusion, the present paper constructed a machine learning model for predicting undergraduate students' SWB with about 91% accuracy. Meanwhile, important predictors for SWB were displayed and analysed. Personality and depressive symptoms affect both freshmen and sophomores' SWB most. This work provides a new evaluating approach on SWB, and contributes to understand of SWB predictors. The 20-items questionnaire may inspire further simple self-reported SWB measurement, which could benefit individualized happiness detection.

Acknowledgements including declarations

We appreciate the contribution of the members participating in this study. This work was supported by the National Key Research and Development Program [2016YFC0906400, 2016YFC1307000, 2016YFC0905000], the National Nature

Science Foundation of China [81421061, 81361120389], and the Shanghai Key Laboratory of Psychotic Disorders [13dz2260500], the Shanghai Leading Academic Discipline Project [B205], and the Fundamental Research Funds for the Central Universities [16JXRZ01]. The authors have declared that no conflict of interest exists. This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent was obtained from all individual participants included in the study.

REFERENCES

1. Hoyt LT, Chase-Lansdale PL, McDade TW and Adam EK. (2012). Positive youth, healthy adults: does positive well-being in adolescence predict better perceived health and fewer risky health behaviors in young adulthood? J Adolesc Health. 50(1): 66-73.

2. Johnson D, Dupuis G, Piche J, Clayborne Z, and Colman I. (2018). Adult mental health outcomes of adolescent depression: A systematic review. Depress Anxiety. 35(8): 700-716.

3. Acharya L, Jin L, and Collins W. (2018). College life is stressful today – Emerging stressors and depressive symptoms in college students. J Am Coll Health. 1-33.

4. Aine H, Peter K, John G and Laura B. (2018). Depressive Symptoms and Suicidal Ideation among Irish Undergraduate College Students. Issues in Mental Health Nursing. (2): 1-10.

5. Ithnain N, Ghazali, SE and Jaafar N. (2018). Relationship between Smartphone Addiction with Anxiety and Depression among Undergraduate Students in Malaysia. International Journal of Health Science Research. 8: 163-171.

6. Kay N, Li K, Xiao X, Nokkaew N, et al. (2009). Hopelessness and Suicidal Behavior among Chinese, Thai and Korean College Students and Predictive Effects of the World Health Organization's WHOQOL-BREF. Int Electron J Health Educ. 12: 16-32.

7. Uglesic B, Lasic D, Zuljan-Cvitanovic M, Bukovic D, et al. (2014) Prevalence of Depressive Symptoms among College Students and the Influence of Sport Activity. Coll antropol. 38(1): 235-239.

8. Wolanin A, Hong E, Marks D, Panchoo K, et al. (2016). Prevalence of clinically elevated depressive symptoms in college athletes and differences by gender and sport. Br J Sports Med 50(3): 167-171.

9. Ibrahim AK, Kelly SJ, Adams CE and Glazebrook C. (2013). A systematic review of studies of depression prevalence in university students. J Psychiatr Res. 47(3): 391-400.

10. Diener E, Scollon CN and Lucas RE. (2003). The evolving concept of subjective well-being: the multifaceted nature of happiness. Advances in cell aging and gerontology. 15: 187-219.

11. Robertson S, Davies M and Winefield H. (2015). Why weight for happiness? Correlates of BMI and SWB in Australia. Obes Res Clin Pract. 9(6): 609-612.

12. Kido T and Swan M. (2016). Machine Learning and Personal Genome Informatics Contribute to Happiness Sciences and Wellbeing Computing. Paper presented at the Association for the Advancement of Artificial Intelligence

13. Jaques N, Taylor S, Azaria A, Ghandeharioun A, et al. (2015). redicting students' happiness from physiology, phone, mobility, and behavioral data. International Conference on Affective Computing and Intelligent Interaction (ACII). 222-228.

14. Bogomolov A, Lepri B and Pianesi F. (2014). Happiness Recognition from Mobile Phone Data. Paper presented at the International Conference on Social Computing.

15. Saputri TRD and Lee SW. (2015). A Study of Cross-National Differences in Happiness Factors Using Machine Learning Approach. International Journal of Software Engineering and Knowledge Engineering. 25(09n10). 1699-1702.

16. Jatupaiboon N, Pan-ngum S and Israsena P. (2013). Real-time EEG-based happiness detection system. ScientificWorldJournal. 2013(4): 618649.

17. Dietterich TG. (2005). Ensemble Methods in Machine Learning. Proc MCS'2000 Lect Notes Comput Sci. 1857.

18. Rokach L. (2009). Ensemble-based classifiers. Artificial Intelligence Review. 33(1-2): 1-39.

19. Friedman JH. (2001). 1999 Reitz Lecture Greedy Funtion Approximation: A Gradient Boosting Machine. The Annals of Statistics. 29(5): 1189-1232.

20. Ford TE, Lappi SK and Holden CJ. (2016). Personality,

DOI: https://doi.org/10.30654/MJPMH.10021

Humor Styles and Happiness: Happy People Have Positive Humor Styles. Eur J Psychol. 12(3): 320-337.

21. Hills P and Argyle M. (2002). The Oxford Happiness Questionnaire: a compact scale for the measurement of psychological well-being. Personality and Individual Differences 33. 1073-1082.

22. Cheng H and Furnham A. (2003). Personality, self-esteem, and demographic predictions of happiness and depression. Personality and Individual Differences. 34. 921-942.

23. Ford BQ, Shallcross AJ, Mauss IB, Floerke VA et al. (2014). Desperately Seeking Happiness: Valuing Happiness Is Associated with Symptoms and Diagnosis of Depression. J Soc Clin Psychol. 33(10): 890-905.

24. Cai N, Bigdeli TB, Kretzschmar W, Li Y, et al. (2015). Sparse whole-genome sequencing identifies two loci for major depressive disorder. Nature. 523(7562): 588-591.

25. Okbay A, Baselmans BM, De Neve JE, Turley P, et al. (2016). Genetic variants associated with subjective well-being, depressive symptoms, and neuroticism identified through genome-wide analyses. Nat Genet. 48(6): 624-633.

26. Fava GA, Cosci F, Guidi J and Tomba E. (2017). Well-being therapy in depression: New insights into the role of psychological well-being in the clinical process. Depress Anxiety. 34(9): 801-808.

27. González Gutiérrez JL, Jiménez BM, Hernández EG and Puente CPA. (2005). Personality and subjective well-being: big five correlates and demographic variables. Personality and Individual Differences. 38(7): 1561-1569.

28. Costa PT and McCrae RR. (1980). Influence of extraversion and neuroticism on subjective well-being: Happy and unhappy people. Journal of Personality and Social Psychology. 38(4): 668-678.

29. Mihaly C. (1990). Flow: The Psychology of Optimal Experience New York: Harper Collins.

30. Seifert T and Hedderson C. (2010). Intrinsic Motivation and Flow in Skateboarding: An Ethnographic Study. Journal of Happiness Study. 11. 277-292.

DOI: https://doi.org/10.30654/MJPMH.10021