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Prediction of problematic social media use (PSU) using machine learning approaches

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Abstract

In this study, problematic social media use (PSU) was modeled using machine learning with artificial neural networks (ANN) and support vector machines (SVM). Fifteen predictor variables were examined in predicting PSU, including social media usage habits (frequency of daily social media use, history of social media usage, frequency of checking social media accounts, number of shares on social media, and number of social media accounts), desire for being liked, envy of the life of others, narcissistic personality traits (exhibitionism, grandiose fantasies, manipulativeness, thrill-seeking, narcissistic admiration and narcissistic rivalry), fear of missing out (FOMO), and online socialization. The present study comprised 309 (208 females and 101 males) university students. Using ANN and SVM, estimation was performed using k-folds (k = 5) cross validation. Results demonstrated a large relationship between predictors and PSU scores. Estimation rates with ANN and SVM were each .61. Then we used forward selection procedures to determine variable importance. We found that frequency of daily social media use, frequency of checking social media accounts, desire for being liked, exhibitionism and FOMO were the five most important variables in association with PSU severity. Finally, we analyzed the extent to which these five variables predicted PSU, finding that the estimate with five variables had a higher coefficient of estimation than with the fifteen variables. Prediction rates for the five variables were .62 using ANN and .63 using SVM. Results demonstrate that several psychological and social media-related variables were important in modeling PSU severity.

Keywords Social media · Problematic social media use · Machine learning · Artificial neural networks · Support vector machine

Introduction

Social media use has become increasingly widespread throughout the world. As of 2019, 45% of the world's population were active mobile social media users (Kemp 2019), and daily average global social media usage was 2 h 16 min (Kemp 2019). As use of social media has become widespread, abuse of social media has also increased. Indeed, social media addiction (Andreassen et al. 2017; Savci and Aysan 2017), social media disorder (Savci and Aysan 2018), excessive use of social media (Griffiths and Szabo 2014), problematic social media use (Meena et al. 2012), compulsive use of social media (De Cock et al. 2014) and pathological use of social media (Holmgren and Coyne 2017) are conceptualized as problems involving abuse of social media. Although these problems are conceptualized with different labels, they point to the same problem. In this paper, we will generally use the concept of problematic social media use (PSU). The intersection of these problems is salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse (Griffiths 2013). As a result, although different concepts are used, PSU is conceptualized as a behavioral addiction (Ercengiz 2019; Griffiths 2013; Griffiths et al. 2014; Savci 2019; Savci and Aysan 2018).

PSU has been defined as the problematic, excessive use of social media comprising (i) an increase over time in the desire to use social media, (ii) important educational and/or occupational activities being neglected, (iii) harming of personal relationships, (iv) using social media to escape from daily life

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stress and negative emotions, (v) experiencing problems in reducing or stopping social media use, (vi) becoming tense and irritable when social media cannot be used, and (vii) lying about the duration of social media use (Griffiths et al. 2014; Griffiths 2013; Kuss and Griffiths 2011a, b; Savci and Aysan 2018; van den Eijnden, Lemmens and Valkenburg 2016). We do not claim that social media use is completely harmful. However, despite the many uses and advantages of social media, there are disadvantages (Elhai et al. 2017). The difference between PSU and non-problematic social media use (non-PSU) usage can be determined by criteria in this definition. PSU causes deterioration in personal, social and professional functioning (Griffiths et al. 2014). On the other hand, non-PSU contributes to the development of social skills (Mariano et al. 2018) and the establishment of new social relationships (Savci and Aysan 2018).

We should note that PSU has not yet been officially recognized as a disorder. However, PSU has similarities to chemical addictions in terms of mood modification, tolerance and withdrawal symptoms (Echeburúa and de Corral 2010; He et al. 2017; Hormes et al. 2014) and behavioral addictions (Griffiths 2013; Griffiths and Szabo 2014; Kuss and Griffiths 2011a; van den Eijnden et al. 2016). In this context, and because internet gaming disorder is now an official diagnosis [World Health Organization (WHO) 2019] it is foreseen that PSU will attract attention of diagnostic authorities in the future.

In this research study, several inclusion criteria were used when selecting the predictor variables. Firstly, we selected predictor variables after conducting a comprehensive literature review focused on risk factors for PSU. In the second stage, we examined whether there are Turkish language versions of the psychological scales measuring these risk factor variables, aiming to use as many predictor variables as possible. Therefore, in this study, we examined PSU severity in association with numerous risk factor variables in the Turkish language. Social media usage habits, desire for being liked, envy of the life of others, narcissistic personality traits (exhibitionism, grandiose fantasies, manipulativeness, thrill-seeking, narcissistic admiration and narcissistic rivalry), fear of missing out (FOMO) and online socialization are demonstrated as risk factors for PSU severity (Carvalho and Pianowski 2017; Marino et al. 2018; Seabrook et al. 2016).

First of all, social media usage habits (frequency of daily social media use, history of social media usage, frequency of checking social media accounts, number of shares on social media, and number of social media accounts) are found to be critical risk factors for PSU severity (Chung et al. 2019; Huang 2017; Kuss and Griffiths 2011a, 2011b; Savci and Aysan 2018; Savci et al. 2018; Savci and Griffiths 2019; Subrahmanyam et al. 2008; van den Eijnden et al. 2016). In addition, frequency of daily social media use (van den Eijnden et al. 2016), frequency of checking social media accounts (Savci and Griffiths 2019), and history of social media usage (Savci et al. 2018) make important contributions to distinguishing between PSU from non-PSU.

Secondly, desire for being liked is considered a factor for PSU (Coulthard and Ogden 2018; Rosenthal-von der Pütten et al. 2019; Sherman et al. 2018). Social media environments are those where individuals can easily present an idealized personality (Blumer and Döring 2012; Hongladarom 2011; Luppicini and Haghi 2012; Manago et al. 2008). Therefore use of social media is closely related to the desire for being liked. Online environments are also frequently used by individuals as a medium to present their appearance and/or idealized appearance (Brown and Knight 2015; Chae 2017; Hogue and Mills 2019), to be the center of attention (Chua and Chang 2016; Mills et al. 2018; Ramsey and Horan 2018), to be liked (Coulthard and Ogden 2018; Rosenthal-von der Pütten et al. 2019; Sherman et al. 2018), to reflect sexual attraction (Ramsey and Horan 2018; van Oosten et al. 2018; van Oosten and Vandenbosch 2017) and to impress others (Weeks et al. 2015; Qiu et al. 2015). In this context, social media can easily satisfy one's desire for being liked.

Thirdly, envy of the life of others is considered a risk factor for PSU (Appel et al. 2015; Lin et al. 2018; Tandoc et al. 2015). Seeing that others are seemingly better off than oneself is aversive for most people (Appel et al. 2015; Jordan et al. 2010). Social media environments are environments where a perfect life can be easily presented (even if deceitful). Social network users often share positive news such as their traveling experiences or newly purchased gadgets or products (Lin et al. 2018). Research shows that individuals who are exposed to attractive profiles have a sense of envy (Appel et al. 2015; Lin et al. 2018).

Fourthly, narcissistic personality traits are considered a risk factor for PSU (Andreassen et al. 2017; Davenport et al. 2014; Hawk et al. 2019; Savci et al. 2019; Wang 2017). Among narcissistic personality traits, exhibitionism (Barry and McDougall 2018; Guo et al. 2018; Hollenbaugh and Ferris 2014; Leung 2013; Ryan and Xenos 2011), grandiose fantasies (Casale et al. 2016; McCain and Campbell 2018; McCain et al. 2016; Singh et al. 2018), manipulativeness (Almuhanna 2017; Craker and March 2016; Fox and Rooney 2015; McCain et al. 2016), thrill seeking (Jensen et al. 2009; Siyez 2014; Sheldon 2012; Wang et al. 2012), narcissistic admiration and rivalry (Seidman et al. 2019; Singh et al. 2018; Sorokowski et al. 2015; Weiser 2015) are found to increase risk for PSU. Therefore, in this study, we took into account these dimensions of narcissism.

Fifth, another risk factor for PSU is the fear of missing out (FOMO) on rewarding social experiences (Blackwell et al. 2017; Casale et al. 2018; Dempsey et al. 2019; Elhai et al. 2018; Franchina et al. 2018; Scott and Woods 2018). Defined as a pervasive apprehension that others might be having rewarding experiences from which one is absent, FOMO is characterized by the desire to stay continually connected with what others are doing (Przybylski et al. 2013, pp. 1841).

Social networking sites can exacerbate FOMO by reminding individuals which experiences they are missing out on in real time (Riordan et al. 2018).

Finally, another important risk factor for PSU is online socialization (Hall 2018; Mariano et al. 2018). Almost every social media application/site is based on creating a profiles and list of online friends/followers. In this aspect, social media primarily advocates virtual or online interaction and socialization, and it can deprive users of the authenticity of real-life human interaction (Mariano et al. 2018). As social media users increasingly develop online social relationships, they become more prone to PSU (Savci and Aysan 2018). Indeed, online social relationships increase the usage time of social media, which is one of the important indicators of PSU.

In this study, we examined variables that are considered risk factors for PSU. Prior work typically analyzed only a limited number of predictor variables in each study. However, in this study we aimed to predict PSU severity using a more comprehensive set of predictor variables. Again, PSU is considered a common and important problem (Masthi et al. 2018; Savci and Griffiths 2019). In addition, the prevalence of PSU increases each day. In fact, PSU is an increasing cause of anxiety in almost all cultures (Hussain and Griffiths 2018). Furthermore, public health concerns about PSU have been voiced by the WHO (2014). Finally, research has shown a potential association between PSU and psychiatric disorders (Hussain and Griffiths 2018). Therefore, the causal mechanisms underlying PSU need to be studied. This study can make critical contributions to the understanding of this modern-day phenomenon, PSU. The most important feature that distinguishes this study from prior work is the prediction of PSU through machine learning, taking into account a broad set of risk factors. In addition, this study can contribute significantly to the prevention of PSU and intervention studies conducted for PSU.

In this study, PSU was predicted using artificial neural networks (ANN) and support vector machines (SVM). Social media usage habits, desire for being liked, envy of the life of others, narcissistic personality traits, FOMO, and online socialization were used as predictors of PSU severity. We modeled PSU scores using fifteen predictor variables associated with social media use. Although these fifteen variables are important for PSU, some variables are thought to be more critical than others. Therefore, we examined which of these fifteen variables are most important.

Methods

Participants

The study comprised 309 university students (208 females and 101 males) who had used social media for at least one year and had at least one social media account, after excluding 23 participants for incomplete, invalid data. The sample consisted of university students studying in various departments. In this research, a convenience sampling method was used for participant recruitment. All data were collected from students at Firat University (Turkey). Demographic data relating to the participants are presented in Table 1.

Materials

The Measures Used Included the Following

Social Media Disorder Scale (SMDS) The SMDS was developed by van den Eijnden et al. (2016) and translated into Turkish by Savci et al. (2018). The scale involves a Likert type scale comprising nine items, and is unidimensional. As a result of Exploratory Factor Analysis (EFA) conducted by Savci et al. (2018), the unidimensional SMDS was found to explain 47.9% of the total variance. This unidimensional structure was tested and supported with Confirmatory Factor Analysis (CFA) in two separate samples (Savci et al. 2018). Cronbach's alpha coefficients of the SMDS were calculated in three different samples, resulting in .83, .86 and .86, and the three-week test-retest correlation was .81. High scores indicate an increased risk of PSU (Savci et al. 2018). In the present study, Cronbach's alpha coefficient was .83.

Desire for Being Liked Scale (DBLS) The DBLS was developed by Kaşıkara and Doğan (2017). The DBLS is a one-dimensional scale comprising nine items and rated on a 4-point scale (1 = I never agree, 4 = I completely agree). As a result of EFA, the unidimensional DBLS explained 42% of the total variance. This unidimensional structure was confirmed by CFA (Kaşıkara and Doğan 2017). Reliability of the DBLS was examined using the test-retest method and Cronbach's alpha coefficients. Test-retest reliability was .73 ($p < .001$).

Table 1 Demographic data of sample ($N = 309$)

Variable	Statistics
Sex	Female = 208 (%67.3) Male = 101 (%32.7)
Age	18–34 age range $\overline{X}$ = 22.21
Daily social media using duration	.15–12 h, $\overline{X}$ = 4.33
Social media using history	1–15 years, $\overline{X}$ = 5.9
Frequency of checking social media accounts	2–360 min, $\overline{X}$ = 71.41
Number of daily shares	0–10 shares, $\overline{X}$ = .73
Number of social media accounts	1–20 accounts, $\overline{X}$ = 4.51
Total	309

Cronbach's alpha coefficients were .82 and .81. High scores on the scale indicate a high level of desire of being liked (Kaşıkara and Doğan 2017). In the present study, Cronbach's alpha was .80.

Subjective Well-Being Scale (SWS) The SWS was developed by Tuzgöl-Dost (2005), a Likert type scale (1 = not suitable at all, 5 = completely suitable) consisting of 46 items and 12 sub-dimensions. As a result of EFA, 12 factors explained 63.83% of the total variance. The SWS was found negatively associated with depression (Tuzgöl-Dost 2005). In test-retest reliability study of the SWS, the relationship between the two testings was.86 ($p < .001$). Cronbach's alpha was .93. High scores in the envy of others' life subscale indicates a high level of envy (Tuzgöl-Dost 2005). In the present study, Cronbach's alpha of the envy of the life of others subscale was .60.

Short Form of the Five-Factor Narcissism Inventory (FFNI-SF) The FFNI-SF was developed by Glover et al. (2012) and translated into Turkish by Eksi (2016). The scale involves a Likert type format (1 = I strongly disagree, 5 = absolutely I agree) comprising sixty items and fifteen sub-dimensions. As a result of CFA, the FFNI-SF showed relatively acceptable fit in a Turkish sample. Cronbach's alpha coefficients of the FFNI-SF range from .57 to .79 (Eksi 2016). In this research, the FFNI-SF's ("exhibitionism", "grandiose fantasies", "manipulativeness" and "thrill seeking" subscales were used. In this study, Cronbach's alpha coefficients were .77 for exhibitionism, .54 for grandiose fantasies, .81 for manipulativeness and .60 for thrill seeking.

Narcissistic Admiration and Rivalry Questionnaire Short Form (NARQ-SF) The NARQ-SF was developed by Back et al. (2013) and translated into Turkish by Demirci and Ekşi (2017). The NARQ-SF consists of six items and two sub-dimensions (admiration and rivalry), rated on a 6-point scale (1 = I never agree, 4 = I completely agree). As a result of CFA, the NARQ-SF had acceptable fit (Demirci and Ekşi 2017). Cronbach's alpha was .72 for the total score, .75 for the admiration sub-dimension, and .62 for rivalry. High scores indicate high levels of narcissistic admiration and rivalry (Demirci and Ekşi 2017). In the present study, Cronbach's coefficients were .65 for narcissistic admiration and .66 for narcissistic rivalry.

Fear of Missing out Scale (FOMO Scale) The FOMO Scale was developed by Przybylski et al. (2013) and translated into Turkish by Gökler et al. (2016). The FOMO Scale consists of ten items, representing a single dimension. The Scale is a Likert type scale (1 = not true at all, 5 = extremely accurate). As a result of EFA, one factor explaining 39.4% of the total variance was evidenced. The test-retest reliability coefficient F was .81 ($p < .001$) (Gökler et al. 2016), and Cronbach's alpha was .81. High scores indicate a high level of FOMO (Gökler et al. 2016). In the present study, Cronbach's alpha was .69.

Virtual Environment Loneliness Scale (VELS) The VELS was developed by Korkmaz et al. (2014). The VELS is a Likert-type scale (1 = not suitable at all, 5 = completely suitable) consisting of 20 items and three sub-dimensions. As a result of EFA, three factors explained 49% of the total variance, confirmed by CFA. The test-retest reliability coefficient was .95 ($p < .001$), and Cronbach's alpha was .82 (Korkmaz et al. 2014). In this research, the 8-item "Virtual Socialization" subscale was used. High scores on the Virtual Socialization subscale indicate a high level of virtual socialization tendency (Korkmaz et al. 2014). In the present study, Cronbach's alpha was .67.

Personal Information Form (PIM) The PIM contains questions related to sex, age, daily social media using duration, social media using history, frequency of checking social media accounts, number of daily shares, and number of social media accounts.

Procedure and Ethics

In the present study, ethics committee approval and application permission were obtained from the first author's university ethics committee. The aim of the study was explained to participants, and written informed consent was provided by all students. The data were collected voluntarily in the students' classes. Use of social media for at least one year was defined as the key inclusion criterion. Students who did not use social media or refused to participate in the study were excluded. Participation lasted approximately 30–35 min.

Data Analysis

In this study modeling PSU, ANN and SVM were conducted. Frequency of daily social media use, history of social media usage, frequency of checking social media accounts, number of shares on social media, number of social media accounts, desire for being liked, envy of the life of others, exhibitionism, grandiose fantasies, manipulativeness, thrill-seeking, narcissistic admiration, narcissistic rivalry, FOMO, and online socialization were used as predictors of PSU severity.

Data mining is generally referred to as an analytic process designed to search a database for consistent patterns and/or systematic relationships between variables, and its ultimate goal is to discover hidden, subtle trends and associations among variables (Grossi et al. 2011). Data mining is used to uncover data patterns, organize information about hidden relationships, configure association rules, estimate the value of unknown items to classify objects, create clusters of homogeneous objects, and reveal many types of findings that cannot be easily produced by a conventional computer-based information system (Peña-Ayala 2014).

ANN and SVM were used in the analysis of data. ANN and SVM are machine learning predictive models of data mining. Machine learning can make predictions by learning rules from the data. Unlike traditional regression models, machine learning algorithms such as ANN and SVM can handle a large number of predictor variables, assess linear and nonlinear relationships in three-dimensional space, overcome multicollinearity non-normality, and accurately assess variable importance through subset selection without sacrificing Type I error (Mullainathan and Spiess 2017; Obermeyer and Emanuel 2016; Tezbaşaran and Gelbal 2018). Because of these powerful features, we used machine learning approaches rather than traditional regression models in this study.

Using both ANN and SVM, prediction was performed using k-folds (k = 5) cross validation. In k-folds cross-validation a dataset X is randomly split into k exclusive subsets X1, …, Xk of approximately equal size and simulations are repeated k times. Each time, one of the k subsets is used as the simulated test set. The other k-1 subsets are combined to form the training set. Then the average error is calculated in all k trials. The advantage of this method is that it is not important how the data is divided. Every data point appears in a simulated test set exactly once, and appears in a training set k-1 times (Sengur 2009). We used the Rapidminer program for data analysis. Three performance measures (Root mean squared error (RMSE), absolute error, and correlation) were used to evaluate ANN and SVM were used. Machine learning approaches for clinical psychology and psychiatry explicitly focus on learning statistical functions from multidimensional data sets to make generalizable predictions about individuals (Dwyer et al. 2018). Although PSU has not been studied using machine learning, Ioannidis et al. (2016) estimated problematic internet use with machine learning approaches. In addition, Elhai et al. (2020) examined problematic smartphone use using machine learning approaches. Therefore, machine learning approaches have been used in the field of problematic internet technology use, but not specifically on problematic social media use.

In this study, PSU, which is the *output variable*, was predicted using our 15 predictor variables. The analysis was performed on the data collected from 309 students. Thus, a matrix data set of 309 × 16 was formed. Prediction of PSU was conducted using ANN and SVM. In both ANN and SVM, prediction was performed using k-folds (k = 5) cross validation. In this section, first, results of ANN and SVM performed with fifteen predictor variables are presented. Then forward selection analysis was performed as a subset selection method for selecting predictors with a stopping rule (Wilkinson and Dallal 1981). This method adds one variable at a time, stopping when it is determined that the remaining predictors will not add significant improvement in the model (Hocking 2013). Therefore, forward selection statistically determines the most important predictor variables. Finally, we present results of ANN and SVM performed with five most important predictor variables determined from forward selection.

Results

ANN consists of an input layer, a hidden layer and an output layer. The learning ratio of ANN was set to .001, the momentum coefficient to .2 and the number of iterations for training was 500. When the performance vector values of ANN were analyzed, the correlation between the data produced by ANN and the real test data was .61. The same prediction was then made using SVM. We found that the correlation between the data produced by SVM and the real test data was .61. The predictions made with both ANN and SVM were thus consistent. ANN and SVM results are presented comparatively in Table 2.

Next, we investigated the most important variables in predicting PSU severity using forward selection. The analysis results are presented in Table 3. Frequency of daily social media use, frequency of checking social media accounts, desire for being liked, exhibitionism and FOMO contributed more to predicting PSU than other variables.

The extent to which these five variables predicted PSU was subsequently examined with ANN and SVM. In both ANN and SVM, prediction was performed using k-folds (k = 5) cross validation. The correlation between the data produced by the ANN model and the real test data was .62. Then the same prediction was conducted for SVM, finding that the correlation between the data produced by SVM and the real test data was .63. ANN and SVM produced consistent results in the five-variable model. ANN and SVM results with five variables are presented in Table 4 comparatively.

Discussion

In this study, we estimated PSU severity from fifteen predictor variables using machine learning approaches (SVM and ANN). We found that a number of variables considered as risk factors for PSU were supported in predicting PSU severity. The prediction results using ANN and SVM are consistent. We also examined which of these risk factors is more predictive. We found that frequency of daily social media use, frequency of checking social media accounts, desire for being liked, exhibitionism and FOMO best predicted PSU severity.

We found that frequency of daily social media use and frequency of checking social media accounts are more predictive variables for PSU than other social media usage habits. In previous studies, these two predictor variables were also identified as important indicators for PSU (Savci et al. 2018; Savci

Table 2 Performance vector values of ANN and SVM

	ANN	SVM
Root mean squared error	5.368 ± .469	5.403 ± .630
Absolute error	4.255 ± .325	4.216 ± .417
Correlation	.608 ± .077	.606 ± .077

and Griffiths 2019; Kuss and Griffiths 2011a, b; van den Eijnden et al. 2016). In fact, most criteria for PSU (such as the amount of use, frequency of use, lying about the frequency of use, needing more use) are related to social media usage habits (Griffiths 2013; van den Eijnden et al. 2016), so such findings make intuitive sense.

We found that the desire for being liked was a strong predictor of PSU severity. Previous studies also found significant associations between PSU and the desire for being liked (Rosenthal-von der Pütten et al. 2019; Sherman et al. 2018). On social media, users can express their favorable attitudes toward messages that others post by clicking the "like" button. In return, they may also receive "likes" from others for their own posts (Hong et al. 2017). Therefore, a user can receive likes from many people on social media in a short time. In this respect, social media environments are unique environments where the desire for being liked can be satisfied. Indeed, social media provide platforms where individuals can be virtually liked, approved, and accepted within a short timeframe (Savci and Aysan 2018). Social media makes it possible to reach crowded groups faster and more efficiently. Therefore, needs of users regarding the desire for being liked is easily met.

Table 3 Results of forward selection analysis

Attribute	Weight
*Frequency of daily social media use	1
History of social media usage	0
*Frequency of checking social media accounts	1
Number of shares on social media	0
Number of social media accounts	0
*Desire for being liked	1
Envy to the life of others	0
*Exhibitionism	1
Grandiose fantasies	0
Manipulativeness	0
Thrill-seeking	0
Narcissistic admiration	0
Narcissistic rivalry	0
*Fear of missing out	1
Online socialization	0

*Variables that make the most important contribution to the estimation

We found that narcissism was a strong positive predictor of PSU severity, consistent with prior work (Barry and McDougall 2018; Casale et al. 2016; Guo et al. 2018; Hollenbaugh and Ferris 2014; Leung 2013; McCain and Campbell 2018; McCain et al. 2016; Ryan and Xenos 2011; Seidman et al. 2019; Singh et al. 2018; Sorokowski et al. 2015; Weiser 2015). However, we assessed narcissism in a multidimensional way using several subscales, finding that the dimension of exhibitionism stood out as the most potent narcissim predictor variable. Individuals with high scores on exhibitionism seek more attention and disclose more self-promoted information online to attract people's attention and appreciation, such as posting self-selected selfies (Guo et al. 2018). In addition, people with high exhibitionism enjoy generate online content by disclosing information about their experiences (Song et al. 2017). According to Kaplan (2012), social networking technology may even satisfy a hidden need for exhibitionism, to post where you are right now and see whether people react by joining you in real time. Online self-sexualization (Ramsey and Horan 2018), selfie-sharing (Qiu et al. 2015), self-disclosure (Hollenbaugh and Ferris 2014) and posting photos of oneself and status updates (Carpenter 2012) can be considered types of exhibitionism.

Finally, we found that FOMO was an important predictor of PSU severity, supporting prior work (Blackwell et al. 2017; Casale et al. 2018; Dempsey et al. 2019; Fuster et al. 2017). FOMO can be identified as an intra-personal trait that drives people to stay up to date on what other people are doing, among others on social media platforms (Franchina et al. 2018). Therefore, FOMO increases exposure to social media (Przybylski et al. 2013). Increased social media exposure causes PSU (Kuss and Griffiths 2011a, b; Savci and Aysan 2018; Savci and Griffiths 2019).

Strengths, Limitations, and Future Research

In this study, first of all, variables that may be related to PSU were investigated in detail. Then, we assessed the extent to which these variables were associated with PSU severity. Finally, the most important variables in predicting PSU were determined. This study conducted an in-depth and detailed investigation of PSU severity, using a more comprehensive set of predictor variables than used before, using more

Table 4 Performance vector values of the ANN and SVM (five-variable)

	ANN	SVM
Root mean squared error	5.298 ± .531	5.322 ± .581
Absolute error	4.192 ± .439	4.128 ± .448
Correlation	0.617 ± .072	0.625 ± .068

sophisticated analyses involving machine learning. Our study clarifies the features that should be intervened in clinical situations in particular. However, self-report measurement tools were used in this study, representing a limitation. Furthermore, data were collected using a convenience sampling method. Finally, the sample had more women than men. In subsequent studies, measurement tools that provide more objective data rather than self-report scales can be used. In addition, reliability of the study can be increased by using a random sampling method. The random sampling method can create a more heterogeneous sample in the distribution of women and men.

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