THE TURKISH JOURNAL ON ADDICTIONS

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ORIGINAL RESEARCH

Use of Network Psychometrics Approach to Examine Social Media Disorder Symptoms

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Main Points

- The symptoms withdrawal, tolerance and preoccupation were observed as the most important ones when dealing with social media disorder.
- Gender and based differences were observed for network structure of social media disorder.
- Deception was observed as the least important symptom when dealing with social media disorder.

Abstract

The symptoms of behavioral addiction are generally regarded as a consequence of a latent construct. However, network psychometrics enable conceptualizing them as directly interacting with variables in a network of symptoms. In this study, it was aimed to investigate symptoms of social media disorder within this framework. This is the first study performed using this novel in the field of behavioral addiction, and conceptualizing social media disorder in this manner helps the professionals in gaining new insights on the construct. The data were collected by applying the Short Social Media Disorder Scale to 727 university students and were analyzed with qgraph and EstimateGroupNetwork packages in R program. Strength, closeness, and betweenness centrality indices were used to evaluate the most important symptoms in the network. The centrality of the network model was further investigated with Zhang's clustering coefficient and the small-world Index was calculated. Finally, the estimated network structures were compared based on gender and age variables. According to the results, withdrawal and preoccupation were detected as the most important symptoms, whereas deception was less important. In addition, it was found that the estimated network had a small-world property. These findings were discussed in terms of their theoretical and practical significance.
Keywords: Addictive behavior, psychometrics, social media, students, Turkey

Introduction

The symptoms of social media disorder (SMD) (such as preoccupation, tolerance, and withdrawal) have been conceptualized and structurally described as being triggered by a common latent variable (van den Eijnden et al., 2016). In network modeling, however, these symptoms are presumed to mutually activate each other (for example, preoccupation causes intolerance, intolerance causes withdrawal, and so on) and they are believed to have independent causal power, not just passive consequences of a common latent cause (Borsboom, 2017).

Briefly, a network is an abstract model containing a series of nodes and edges that connect the nodes in addition to some information about the nature of nodes and edges. The nodes represent elements/entities, and the edges represent interactions (Kolaczyk, 2009). The nodes correspond to the symptoms, items, or sub-dimensions in an assessment tool that measures psychological traits (Klippel et al., 2018). The edge weights are represented by the thickness of the lines connecting the nodes. In addition, the color of the line differs depending on whether the relationship is positive or negative (red color for negative relationships and green or blue color for positive relationships) (Epskamp et al., 2012).

In psychological network models, direct relationships between symptoms are thought to explain the co-occurrence of those symptoms. For example, if individ-

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Received: December 12, 2020
Accepted: April 13, 2021

Cite this article as: Avcu, A. (2021). Use of network psychometrics approach to examine social media disorder symptoms. *Addicta: The Turkish Journal on Addictions, 8*(1), 87-91.

DOI: 10.5152/ADDICTA.2021.20098

uals have sleep problems, they also have concentration problems or are reluctant to start a new task (Fried et al., 2015). Researchers can get precise information about multivariate dependencies in the data by visualizing the graph after estimating the network structure. Furthermore, different inferential approaches may be used to determine which node is more important or central.

Due to these promising properties of the network modeling approach, several studies in the field of psychology have been conducted so far to uncover the network structure of psychological variables (e.g., McElroy et al., 2018; Santos et al., 2017). Despite the great potential of network modeling, only one study in the field of behavioral addiction was conducted so far (Rozgonjuk et al., 2020) that aimed to investigate associations between symptoms of problematic smartphone, Facebook, WhatsApp, and Instagram use. To address this gap in the literature, the current study aimed to use network psychometrics to examine symptoms of SMD. Examining SMD symptoms in the context of network analysis will provide new insights to our existing understanding of the construct.

Introducing Psychometric Network Analysis

When the data consists of polytomous items, the networks are estimated using the Gaussian Graphical Models (GGM) proposed by Foygel and Drton (2010). The strength of an edge corresponds to the extent of association between two nodes after controlling for the effects of other nodes in the network; that is, edge weights are expressed in terms of partial correlations in the GGMs (McNally et al., 2015). The weight strength of a network edge corresponds to the partial correlation coefficient (Epskamp et al., 2012). After partial correlations are estimated, they are visualized in a weighted network structure. If the partial correlations are exactly zero, no edge is drawn between the corresponding pair of nodes and implies the conditional independence of these nodes. However, it is almost impossible to obtain a partial correlation value of zero for any two variables in an observed data set due to sampling variation. Therefore, filtering must be performed to minimize spurious connections and increase the interpretability of the network. The most commonly used filtering method is the Least Absolute Shrinkage and Selection Operator (LASSO), which has been recommended for psychometric data (Epskamp et al., 2018). The main goal for using LASSO is to achieve more parsimonious (or sparse) network structures. Therefore, a researcher can be more confident that when an edge is drawn between two nodes, there is indeed an association in the network (Krämer et al., 2009). The optimal model is generally selected by a tuning parameter that minimizes the extended Bayesian Information Criterion (EBIC), as proposed by Chen and Chen (2008). This tuning parameter is used to control the sparsity of the estimated network. It has been reported that minimizing EBIC works well in estimating sparse networks and reproduces the true network structures (van Borkulo et al., 2014).

In addition, it is possible to compare estimated networks by subgroups using Joint Gaussian Graphical Models (Danaher et al., 2014). After examining the structural properties of the network, the next step is usually to identify the most influential nodes. This process is achieved by using centrality indices (Costantini et al., 2015). Centrality generally refers to a set of indices that quantitatively represent the relative importance of a node in a network compared to other nodes (Freeman, 1978). Centrality has attracted considerable attention in the psychology literature as a means of assessing the most influential symptoms of psychopathological disorders (Wigman et al., 2015). Three of these centrality indices are recommended for use in assessments for psychological networks (Opsahl et al., 2010): strength, closeness, and betweenness. The strength index indicates how well a node is directly connected to other nodes in the network. The closeness index indicates how well a node is indirectly connected to other nodes. Finally, the betweenness shows how important a node is in the average path between two nodes.

Methods

Participants

For the research, approval was obtained from Marmara University, Institute of Educational Sciences, Research and Publication Ethics Committee on Nov 19, 2020 (No: 2000310221). Participants were selected from four different state universities located in a major metropolitan city in Turkey. A large representative group of participants was included in the study (n=727). They consisted of 590 (81.2%) females and 137 (18.8%) males with ages ranging from 16 to 23 (mean=21.23, SD=1.66) years. Data were collected through an online data collection platform due to the 2020 pandemic outbreak.

Measures

Short Nine-Item Social Media Disorder Scale

Short version of SMD scale (S-SMDS) was developed by van den Eijnden et al. (2016). The scale assesses SMD using the following nine different diagnostic criteria: Preoccupation, Tolerance, Withdrawal, Displacement, Escape, Problems, Deception, Displacement, and Conflict. These criteria are based on the diagnostic criteria found at Internet Gaming Disorder, which are included in the fifth edition of the Diagnostic and Statistical Manual for Mental Disorders (DSM-V). The total scale consists of 9 items. It was reported that S-SMDS has a unidimensional structure [$X^2(27)=24.85$, $p=0.58$, CFI=1.000, RMSEA=0.000] and good reliability level. The adaptation of the Turkish version of the S-SMDS for university students was performed by Avcu et al. (2019). The unidimensional structure of the original version was also confirmed in the Turkish version.

Statistical Analysis

The R statistical program was used throughout the analysis process (R Core Team, 2019). The network structure of symptoms in the S-SMDS was estimated using the GLASSO model. The tuning parameter for this study was set to 0.5 to obtain a sparser and interpretable network structure, as suggested by Friedman et al. (2010). Centrality indices (strength, closeness, and betweenness) were calculated to identify central and peripheral symptoms. In addition, Zhang's cluster coefficient, Onnela's cluster coefficient, Watts and Strogatz's cluster coefficient, and Barrat's clustering coefficient were calculated to evaluate interconnectedness of the network (Epskamp et al., 2018). Costantini and Perugini (2014), however, found that Zhang's clustering coefficient was less affected by variations in the network and gave more stable results. Only the results for this coefficient were reported. All the above analyzes were performed using the qgraph package (Epskamp et al., 2012). Finally, using the joint GLASSO method (Danaher et al., 2014), network structures were estimated simultaneously for the subgroups according to the variables of gender (male vs. female) and age (⩽20 years vs. ⩾21 years), and the differences in these estimated models were presented. This process was performed using the EstimateGroupNetwork package available in the R environment (Costantini et al., 2019).

Results

The GGM based network model of SMD was estimated. For this analysis, the Fruchterman-Reingold algorithm was used to place the nodes in the network such that more important nodes were placed in a more central position (Fruchterman & Reingold, 1991). The graph of the estimated network is shown in Figure 1. As can be seen, the symptoms differed in their connections with other symptoms. Particularly strong connections were observed between tolerance-persistence and persistence-retreatment symptom pairs. In addition, problems, deception, and conflict symptom trio had strong connections among themselves but relatively weaker connections with other nodes in the network. Similarly, the displacement-persistence-escape symptom trio had strong connections with each other, while they also had relatively stronger connections with the tolerance-persistence-withdrawal symptom trio.

Another point worthy of attention in the estimated network is that the tolerance-preoccupation-withdrawal symptom triple was more centrally located in the graph and more strongly connected. The connections between the problems-deception-conflict

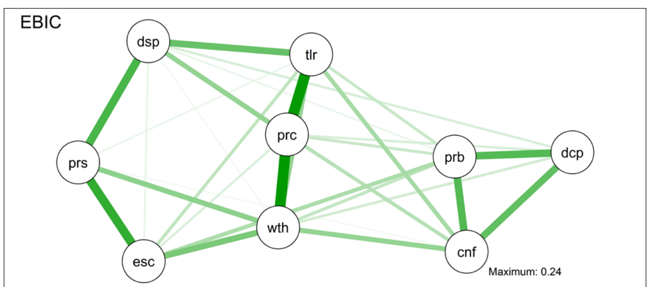

Figure 1. Network Analysis of S-SMDS Items. The Size and Density of the Edges between the Nodes Represent the Strength of Connectedness. Green Colored Edges Correspond to Positive Associations
tlr: tolerance; prc: preoccupation; wth: withdrawal; dsp: displacement; prs: persistence; esc: escape; prb: problems; dcp: deception; cnf: conflict.

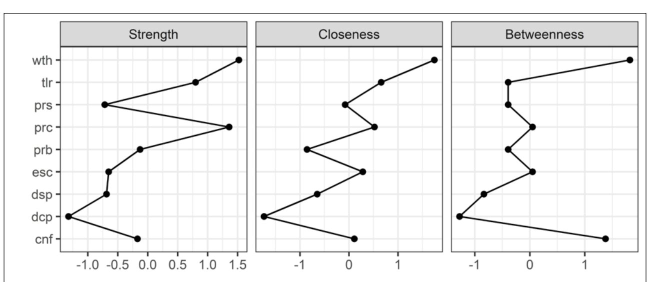

Figure 2. Centrality Indices for S-SMDS Items. The Line Graph was Drawn on the Basis of Standardized Indices
Note. On the Y axes, tlr: tolerance; prc: preoccupation; wth: withdrawal; dsp: displacement; prs: persistence; esc: escape; prb: problems; dcp: deception; cnf: conflict.

and displacement-persistence-escape symptom triplets, which were relatively distant in the network.

Computing Centrality Measures

The findings of centrality indices are provided in Figure 2. In this figure, there are line graphs showing the values of the strength, closeness, and betweenness centrality indices for each item of S-SMDS. All of these index values are standardized and located on a common scale to facilitate the interpretation.

The highest strength values belonged to withdrawal and preoccupation symptoms and the lowest values to deception and displacement. According to this result, it can be inferred that the symptoms in the most central position for the SMD latent trait were detected as withdrawal and preoccupation. In addition, they were the most important symptoms and have higher influence on other symptoms. It implies that if withdrawal and preoccupation symptoms are observed in an individual, the other symptoms can be expected to activate over time.

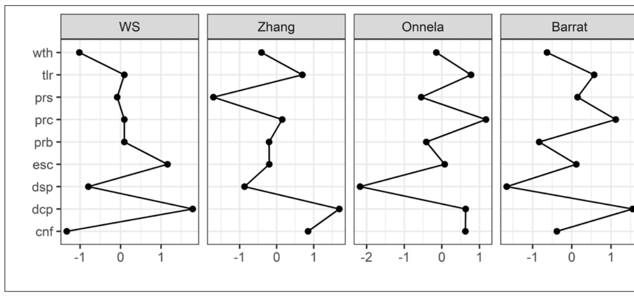

Figure 3. Clustering Coefficients Plot of S-SMDS Items
Note. WS: Watts and Strogatz's cluster coefficient; Barrat: Barrat's clustering; Zhang: Zhang's clustering coefficient; Onnela: Onnela's clustering coefficient. On the Y axes, tlr: tolerance; prc: preoccupation; wth: withdrawal; dsp: displacement; prs: persistence; esc: escape; prb: problems; dcp: deception; cnf: conflict.

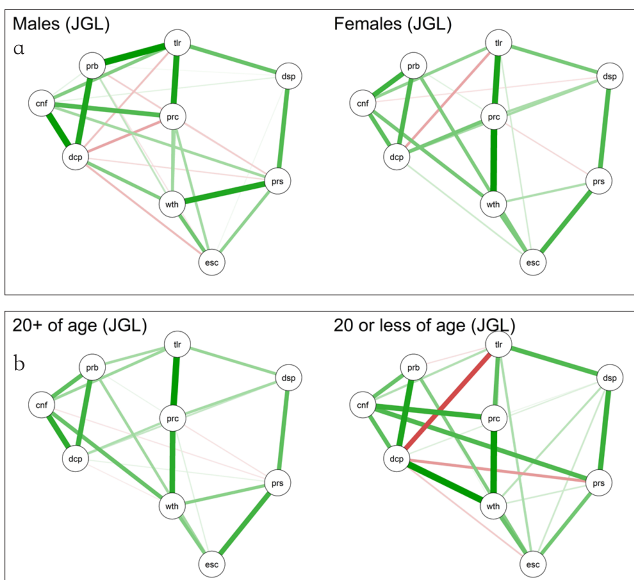

Figure 4. a, b. Estimated Network Models by Joint Graphic Least Absolute Shrinkage and Selection Operator Models for Age and Gender Variables. Green Colored Edges Correspond to Positive Associations, and Red Colored Edges Correspond to Negative Associations.

Regarding the closeness index, the figure shows that the node with the highest value of closeness was withdrawal. Thus, this symptom can be expected to be a good predictor for the other symptoms. Finally, when the betweenness centrality index of SMD symptoms were examined, it was seen that the highest index values were estimated for withdrawal and conflict symptoms. This finding is an indication that these two symptoms are the intermediate symptoms that connect the other symptom pairs more and have connection with more nodes. Conversely, it was found that the deception symptom had the lowest values for all the centrality indices. Its increased level does not trigger any other symptoms and does not deserve close attention or during.

In addition to the centrality indices, clustering coefficients were also calculated. Clustering coefficients are indicative of how many possible connections are estimated across neighbor symptoms of a symptom of interest (Watts & Strogatz, 1998). These coefficients also show how important a symptom is in connecting other networks and contributing to the network. The line graph showing the standardized clustering coefficients for each SDMS symptom is presented in Figure 3. On the basis of Zhang's clustering coefficients, the highest clustering coefficient values were obtained for the deception symptom, whereas the lowest clustering coefficient was for the persistence symptom. This result suggested that the deception symptom contributed little to the interconnectedness of its neighbors, whereas persistence contributed the most.

Finally, as an indication of the Global index of interconnectedness, the small-world Index was also calculated for the estimated network model. This index value shows how high a network has coefficients and average path length in clusters (Watts & Strogatz, 1998). The small-world networks have dense connections between nodes and links that connect relatively remote nodes in the network. If the Small-World Index is > 1, it is considered to be the indicator of being the small-world network (Humphries & Gurney, 2008). The small-world index value for S-SMDS data was estimated as 1.27. This finding shows that the SMD network has the property of small-worldedness, which implies that SMD symptoms are sufficiently interconnected at the local level.

Comparing the SMD Network Across Subgroups

A joint LASSO model was used to determine how the estimated GLASSO network model is different across subgroups within the sample. For this analysis, gender (male/female) and age ($\leqslant$ 20 to $\geqslant$ 21 years) variables were used. Overall, figures 4a and 4b suggest that the estimated network structure for the total sample group is similar accross age and gender sub-groups. The location of central and peripheral symptoms has not changed. However, differences were observed in the edges connecting symptoms across sub-groups.

Discussion

In this study, it was aimed to examine the symptoms of S-SMDS using network analysis. This study is important in terms of being one of the first studies using the network psychometrics approach in the field of behavioral addictions. Using the network analysis, we examined how the network pattern of the SMD symptoms were interconnected; which was the most central and least central in the estimated network pattern; and differences of the predicted network pattern by age and sex. As a result of these findings, important conclusions were reached for professionals performing the clinical evaluation.

The most important benefit in examining the symptoms using network analysis is to see which symptoms are indicators of psychological disorders and which are clinically more important. In addition, the association patterns between them can provide important implications. These results can also elicit several hypotheses for further studies. From this point of view, this study presented important findings. For example, it was determined that the most effective (central) symptoms were withdrawal, tolerance, and preoccupation. These symptoms were also among the most underlined symptoms for (Marks, 1990) and traditionally regarded as the core symptoms of behavioral addictions. However, deception, displacement, and conflict symptoms were added later to the internet gaming disorder diagnostic criteria in the fifth edition of Diagnostic and Statistical Manual for Mental Disorders (2013) and used for developing S-SMDS used in this study. In this study, deception symptom was found as the least central and influential symptom. Therefore, using network analysis, it was confirmed that the first six behavioral addiction criteria of internet gaming disorder were of central importance in behavioral addiction; whereas deception, which was added later, was the less important one.

In addition, when the graphical representation of the network model was examined, it was found that withdrawal, preoccupation, and tolerance symptoms were at the most central location. Therefore, mental health professionals who carry out clinical interventions should first focus on and emphasize these three most central symptoms. As deception was estimated as the most peripheral symptom; during clinical interventions, lying is the symptom that should be least emphasized for treatment.

Limitations and Directions/Suggestions for Future Research

This study had certain limitations. Cross-sectional data were used, which meant it was not possible to make causal inferences. Longitudinal data is required to better understand the dynamic system of symptoms, and network analysis should be estimated at the longitudinal level (Epskamp et al., 2018). In future studies, it is recommended to perform network estimation using longitudinal data. Another limitation was that the data of this study were collected from university students. Therefore, it is suggested to replicate this study with different populations and clinical groups and investigate how it will affect the pattern of relationships between symptoms, and which symptoms will be the most central symptoms. Finally, the data were collected via an online platform because of the 2020 pandemic outbreak. Hence, strict sampling procedures were not applied to increase the generalizability of the results.

Ethics Committee Approval: Ethics committee approval was received for this study from Marmara University, Institute of Educational Sciences, Research and Publication Ethics Committee on Nov 19, 2020 (No: 2000310221).

Informed Consent: Written informed consent was obtained from all participants who participated in this study.

Peer-review: Externally peer-reviewed.

Conflict of Interest: The author has no conflicts of interest to declare.

Financial Disclosure: The author declared that this study has received no financial support.

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