Work Addiction and Work Engagement: A Network Approach to Cross-Cultural Data

Piotr Bereznowski, Aleksandra Bereznowska, Paweł Andrzej Atroszko, Roman Konarski

University of Gdańsk

Abstract

This study aimed to investigate direct relationships of work addiction symptoms with dimensions of work engagement. We used three samples in which work addiction was measured with the Bergen Work Addiction Scale and work engagement was measured with the Utrecht Work Engagement Scale. One sample comprised responses from working Norwegians ($n_1 = 776$) and two samples comprised responses from working Poles ($n_2 = 719$; $n_3 = 715$). We jointly estimated three networks using the fused graphic lasso method. Additionally, we estimated the stability of each network, node centrality, node predictability, and quantitatively compared all networks. The results showed that absorption and mood modification could constitute a bridge between work addiction and work engagement. It suggests that further investigation of properties of absorption and mood modification might be crucial for answering the question of how engaged workers become addicted to work.

Keywords: compulsive overworking, network analysis, network approach, work addiction, work engagement, workaholism

Introduction

The network approach to psychopathology (formalized as the network theory of mental disorders; Borsboom, 2017) has become a popular framework for studying mental disorders (Contreras et al., 2019; Fried et al., 2017; Robinaugh et al., 2020). Recently, it has been used to conceptualize work addiction as a dynamic system of symptoms in direct relationships (Bereznowski et al., 2021). This paper aims to extend the previous work by investigating direct relationships of work addiction symptoms with dimensions of work engagement in three samples with diverse cultural and sociodemographic backgrounds (one Norwegian sample and two Polish samples).

The Network Approach to Psychological Data

A network is a graph consisting of nodes and edges. Nodes represent observed variables (e.g., a symptom of work addiction or a dimension of work engagement). Edges represent direct relationships between nodes estimated from data (e.g., partial correlation coefficients). Network analysis is a multistep process of analyzing a pattern of edges present in the network (Epskamp et al., 2018). The first step includes investigating which edges connect nodes, whether the edges are positive or negative, how strong they are, and search for clusters of nodes in the network (i.e., groups of strongly connected nodes). The second step includes investigating the stability of estimated networks which indicates whether a third step (network inference) is warranted. The third step includes an investigation of nodes centrality (i.e., how strongly a node could influence and/or be influenced by all other nodes in the network; Epskamp et al., 2018) and nodes predictability (i.e., how much a node can be predicted by all the other nodes in the network; Haslbeck & Waldorp, 2018). The fourth step (performed only when several networks were estimated) includes an investigation of the difference between the estimated networks. According to the network theory of mental disorders, the results of network analysis could provide information for the development of treatment and prevention programs (Borsboom, 2017).

The Network Approach to Work Addiction

A recent debate showed that there is a consensus between experts that compulsive overworking is a genuine problem (Andreassen et al., 2018; Atroszko et al., 2019; Griffiths et al., 2018; Kun, 2018; Lior et al., 2018; Malinowska, 2018; Quinones, 2018; Sussman, 2018; Tóth-Király et al., 2018). Over the years, several conceptualizations of this phenomenon were proposed in the literature (e.g., Clark et al., 2020; Loscalzo & Giannini, 2018; Snir & Harpaz, 2012; Vallerand et al., 2010), including the one conceptualizing compulsive overworking within a behavioral addictions framework and labeling it work addiction (Griffiths, 2011; Griffiths et al., 2018). The work addiction conceptualization is based on a common addiction components model (Brown, 1993; Griffiths, 2005), which includes seven addiction symptoms.

As the interpretation of network analysis is inseparably tied to the operationalization and measurement (Burger et al., 2020; Fried, 2017; see also Malgaroli et al., 2021; Rodebaugh et al., 2018), we devote the following paragraph to describe the seven symptoms of work addiction in detail.

Salience (1) refers to the constant preoccupation with work, which manifests itself in the dominance of work in the individual's thoughts, feelings, and behavior. *Tolerance* (2) refers to the need to increase the amount of work to achieve the previous mood modification effects and means that the individual gradually increases the amount of time spent every day working. *Mood modification* (3) refers to the subjective experience that working allows the individual to escape the negative states that he/she is experiencing (e.g., anxiety, guilt, or hopelessness) or to experience the arousing "high" associated with working. *Relapse* (4) refers to the repeated reversions to earlier patterns of excessive working (which are quickly restored even for the most extreme patterns) after periods of control. *Withdrawal* (5) refers to the unpleasant affective states and/or physical effects when the individual is unable to work. *Conflict* (6) refers to the conflicts between the individual and those around them, the conflicts between work

and other activities such as social life and hobbies, and intrapsychic conflicts such as incompatible needs. *Problems* (7) component refers to the health and/or other problems resulting from excessive working (Andreassen et al., 2012; Griffiths, 2011).

A previous study showed that the pattern of direct relationships between symptoms of work addiction was almost identical for individuals of diverse cultural and sociodemographic backgrounds (Bereznowski et al., 2021). In each of the four networks, the most central symptom was relapse, and the least central symptom was mood modification. Additionally, each network of work addiction comprised two clusters of symptoms, which showed partial overlap with a distinction between core and peripheral addiction criteria distinguished for gaming addiction (Charlton & Danforth, 2007). In the case of gaming addiction, the core criteria were conflict, withdrawal symptoms, relapse and reinstatement, and behavioral salience and the peripheral criteria were cognitive salience, tolerance, and euphoria (Charlton & Danforth, 2007). In the case of work addiction, the first cluster included tolerance, relapse, conflict, and problems and the second cluster included salience, mood modification, and withdrawal. Taking into account that the same addiction symptoms might have somewhat different diagnostic properties in the case of different behaviors (for differences in diagnostic properties of symptoms between work addiction and gaming addiction, see Bereznowski & Konarski, 2020; Khazaal et al., 2018), these results could indicate that the two clusters represent groups of more (tolerance, relapse, conflict, and problems) and less (salience, mood modification, and withdrawal) pathological symptoms of work addiction. Based on this premise and the positive characteristic of work engagement (Schaufeli et al., 2002), we argue that the less pathological symptoms of work addiction would have direct positive relationships with some dimensions of work engagement in the network of work addiction and work engagement.

Work Addiction and Work Engagement

The most widely adopted conceptualization of work engagement is the one proposed by Schaufeli et al. (2002), which defines work engagement as a work-related mental state characterized by vigor, dedication, and absorption (Baily et al., 2017). *Vigor* (1) refers to "high levels of energy and mental resilience while working, the willingness to invest effort in one's work, and persistence even in the face of difficulties" (Schaufeli et al., 2002, p. 74). *Dedication* (2) refers to "a sense of significance, enthusiasm, inspiration, pride, and challenge" (Schaufeli et al., 2002, p. 74). *Absorption* (3) refers to "being fully concentrated and deeply engrossed in one's work, whereby time passes quickly and one has difficulties with detaching oneself from work" (Schaufeli et al., 2002, p. 75).

While work engagement is regarded as a positive and fulfilling mental state, it also is weakly positively associated with compulsive overworking (Clark et al., 2016; Di Stefano & Gaudiino, 2019). The two recent meta-analyses revealed that this relationship is a result of a weak positive relationship between compulsive overworking and a single dimension of work engagement—absorption (r estimates between compulsive overworking and absorption varied between .09 and .17; Clark et al., 2016; Di Stefano & Gaudiino, 2019; for the detailed comparison of the results of these two studies, see the Supplemental Materials). Thus, the positive relationship between compulsive overworking and absorption could result from the content overlap between absorption and some symptoms of work addiction (Di Stefano & Gaudiino, 2019). Based on the following part of the absorption definition "one has difficulties with detaching oneself from work" (Schaufeli et al., 2002, p. 75), we argue that the content overlap probably involves salience (constant preoccupation with work), tolerance (working longer than initially intended), withdrawal (unpleasant affective states when the individual is unable to work), and conflict (conflicts between the work and other activities such as social life and hobbies). This overlap would be observed in the networks of work addiction and work engagement as direct relationships between absorption and the four symptoms of work addiction. The presence of

these relationships could provide further insights into how engaged workers become addicted to work, and approaching this issue using the network theory framework could contribute to the development of prevention programs based on quantitative evidence (Borsboom, 2017).

The Present Study

The three samples we used in this study are the same samples that Bereznowski et al. (2021) used to investigate direct relationships between symptoms of work addiction. For this reason, our result regarding direct relationships between symptoms of work addiction would closely reflect the results reported by Bereznowski et al. (2021) and should not be taken as novel results; therefore, they will not be discussed in this work.

This study focused on investigating direct relationships between symptoms of work addiction and dimensions of work engagement. We will start by estimating three networks of work addiction and work engagement in which edges between pairs of nodes (a node is either a symptom of work addiction or a dimension of work engagement) would indicate direct relationships between these nodes. Further, we would estimate the stability of these networks and investigate node centrality (indicating how strongly a node could influence and/or be influenced by all other nodes in the network) and node predictability (indicating how much all of its neighbors can predict a node) of all nodes in the networks. Finally, we would compare the three networks and estimate a combined cross-sample network to highlight similarities between the networks and a cross-sample variability network to highlight differences between the networks.

Hypotheses

Based on previous empirical research and theoretical considerations, we formulated the following hypotheses. Hypothesis 1: The networks of work addiction and work engagement would

have three clusters of nodes (Cluster 1: dimensions of work engagement; Cluster 2: salience, mood modification, and withdrawal; Cluster 3: tolerance, relapse, conflict, and problems). Hypothesis 2: Cluster 1 would be connected with Cluster 2 and Cluster 3 via direct relationships between absorption and salience, tolerance, mood modification, withdrawal, and conflict. Based on completely positive characteristics of vigor and dedication and the results of previous studies (Clark et al., 2016; Di Stefano & Gaudiino, 2019), we do not expect any direct relationships between these two dimensions of work engagement and symptoms of work addiction. Hypothesis 3: Due to numerous direct relationships with symptoms of work addiction, absorption would be a central node in the network of work addiction and work engagement, and it would constitute a bridge between the two phenomena.

Method

Participants and Procedure

In this study, we used three samples from research focusing on work addiction; one included responses of working Norwegians (Sample 1), and two included responses of working Poles (Sample 2 and Sample 3). One sample included the general working population (Sample 2), and two samples included individuals of considerably younger age (Sample 1 and Sample 3). The latter samples were recruited for a longitudinal study on work addiction when they were studying at a university in 2013. The analyses included their responses after they graduated and begun working professionally. Their young age and early stage of career are related to important differences in terms of socioeconomic status (education – all university graduates, salary – lower salaries, job position – less likely to have managerial positions, wealth – less likely to accumulate wealth) in comparison to the general working population including older participants (on average more than ten years older) who most notably were not all university graduates. Detailed sociodemographic characteristics of the three samples after listwise deletion of observations with missing data on work addiction or work engagement and their

statistical comparison are presented in Table 1. Detailed information regarding compensation, missing data, and removal of observations with missing data are presented in the Supplemental Materials.

[Table 1 near here]

Measures

Work Addiction

The Bergen Work Addiction Scale (BWAS; Andreassen et al., 2012) consists of seven items based on the seven symptoms of addiction (Brown, 1993; Griffiths, 2005; Leshner, 1997). Each item asks respondents how often they experienced a given symptom during the past 12 months. The responses are provided on a 5-point Likert scale ranging from 1 (*never*) through 2 (*rarely*), 3 (*sometimes*), 4 (*often*) to 5 (*always*). This measure does not have a skip-structure, and we did not preprocess the obtained responses in any way. The Norwegian version of the scale was used in Sample 1, and the Polish version of the scale was used in Sample 2 and Sample 3. The BWAS showed good content validity, convergent validity, and criterion validity in previous studies (for the evidence of the validity of the Norwegian version of the BWAS, see Andreassen et al., 2014; Andreassen et al., 2016; Andreassen et al., 2019; for the evidence of the validity of the Polish version of the BWAS, see Atroszko et al., 2017). The Cronbach's alpha reliability coefficients were .85 for Sample 1, .84 for Sample 2, .84 for Sample 3.

Work Engagement

The 9-item version of the Utrecht Work Engagement Scale (UWES-9; Schaufeli et al., 2006) consists of nine items, three for each dimension of work engagement: vigor, dedication, and absorption. Each item asks respondents how often they experienced a described state during their lifetime. The responses are provided on a 7-point Likert scale ranging from 1 (*never*) through 2 (*a few times a year*

or less), 3 (*once a month or less*), 4 (*a few times a month*), 5 (*once a week*), 6 (*a few times a week*) to 7 (*everyday*). This measure does not have a skip-structure, and we did not preprocess the obtained responses in any other way than obtaining a sum of three items for each dimension. The Norwegian version of the scale was used in Sample 1, and the Polish version of the scale was used in Sample 2 and Sample 3. The UWES showed good content validity, convergent validity, and criterion validity in previous studies (Schaufeli et al., 2006); however, there is mixed support for its factorial validity in different countries (for the evidence of the validity of the Norwegian version of the UWES, see Nerstad et al., 2010; for the evidence of the validity of the Polish version of the UWES, see Kulikowski, 2019). The Cronbach's alpha reliability coefficients were .89 (vigor), .89 (dedication), and .84 (absorption) for Sample 1, .85 (vigor), .82 (dedication), and .78 (absorption) for Sample 2, .84 (vigor), .80 (dedication), and .76 (absorption) for Sample 3.

Sociodemographic Characteristics

In each sample, participants were asked about sex, age, marital status, working hours per week, work status, and gross income (i.e., past year personal annual income before tax). In the case of gross income, participants in Sample 1 and Sample 3 were asked a closed-ended question with different income ranges for each category in each sample (see Table 1), and participants in Sample 2 were asked an open-ended question about their last year's income. Additionally, participants in Sample 1 and Sample 3 were asked about the highest completed level of education and subjective socioeconomic status measured with the MacArthur Scale of Subjective Socioeconomic Status (Adler et al., 2000), which showed good validity and reliability in previous research (Operario et al., 2004).

Statistical Analyses

All analyses were carried out with R version 4.0.5 (R Core Team, 2021) and visualized with the qgraph 1.6.9 package (Epskamp et al., 2012). For estimating networks from multiple samples, we followed the four steps described by Fried et al. (2018): (a) network estimation, (b) network stability, (c) network inference, and (d) network comparison. We followed the reporting standards for psychological network analyses in cross-sectional data set by Burger et al. (2020) for reporting the results. Some important but not essential parts of the method and the results sections (e.g., individually estimated networks and bootstrapped values of edge weights) are available in the Supplemental Materials. The analytic code for all analyses performed in this study and the Supplemental Materials are available at <https://osf.io/r693u/>.

Network Estimation

To jointly estimate the three networks, we used the fused graphic lasso (FGL) method and the EstimateGroupNetwork 0.3.1 package (Costantini & Epskamp, 2017). The optimal values of λ_1 (a tuning parameter regulating the density penalty) and λ_2 (a tuning parameter regulating the penalty on differences among corresponding edge weights between networks from different samples) were selected sequentially via k-fold cross-validation with seed set to 1. A layout for visualizations was obtained via averaging the layouts for the three individually estimated networks. To search for clusters of nodes within the three networks, we used a spin-glass algorithm implemented in the igraph 1.2.6 package (Csardi & Nepusz, 2006).

Network Stability

To investigate the stability of the three networks, we used the bootnet 1.4.7 package (Epskamp et al., 2018), using nonparametric bootstrapping and case bootstrapping based on 1000 bootstrap samples, which estimates stability based on individually estimated networks. As a measure of network

stability, we used the correlation stability coefficient, which represents the maximum proportion of cases that can be dropped, such that with 95% probability, the correlation between original centrality measures and centrality of networks based on subsets is .70 or higher. A correlation stability coefficient higher than .50 is regarded as an indicator of good stability, and a correlation stability coefficient higher than .25 is regarded as an indicator of acceptable stability (Epskamp et al., 2018).

Network Inference

We estimated node centrality based on the node strength. A standard version of the node strength is a metric equal to the sum of absolute values of all edges of a given node to all other nodes. We argue that the standard version of the node strength could poorly identify bridge nodes when tightly connected clusters of nodes are weakly connected with each other. Therefore, we created a modified version of the node strength which should better capture bridge nodes in this special case, we call it a bridge strength. The bridge strength is a metric equal to the sum of absolute values of all edges of a given node to all other nodes which represent different psychological phenomenon (e.g., for absorption this is the sum of absolute values of all edges which absorption has with work addiction symptoms). To compare the three networks in terms of node centrality, we calculated Spearman correlation coefficients between both versions of the node strength for the three pairs of networks.

To estimate the predictability of nodes, we used the *mgm* 1.2-11 package (Haslbeck, 2019), which estimates predictability based on individually estimated networks. For continuous data (dimensions of work engagement), node predictability indicates the percentage of variance explained by all of its neighbours (R^2). For ordinal data (symptoms of work addiction), node predictability indicates how much a node can be predicted by all of its neighbours, beyond what is trivially predicted by the marginal distribution of this node (for a detailed explanation, see Haslbeck & Waldorp, 2018).

Network Comparison

To compare pairs of networks, we calculated Spearman correlation coefficients of edge weights for each pair of networks and used the NetworkComparisonTest 2.2.1 package (van Borkulo et al., 2017) with seed set to 1. Using the NetworkComparisonTest package, we performed the omnibus test, which allows investigating whether all edges of the two networks are identical. When the omnibus test was statistically significant, we performed the post hoc test (which uses the Holm-Bonferroni method to correct for multiple testing) to investigate which edges weights were different between the two networks. Finally, regardless of previous results and for the sake of future comparisons, we calculated the global strength estimates (the sum of all absolute edge weights for each network) and tested whether they differed between networks.

To highlight the similarities between the three networks, we estimated a cross-sample network (obtained by pooling all observations into one sample) and used it to calculate the standard version of the node strength, the bridge strength, and node predictability. To highlight the differences between the three networks, we estimated a cross-sample variability network in which each edge represents the standard deviation of this edge between the three networks (see Fried et al., 2018).

Results

Descriptive Statistics

Means, standard deviations, skewness, and kurtosis of the seven symptoms of work addiction and the three dimensions of work engagement in the three samples are presented in Table 2. The three populations differed significantly in terms of severity of symptomatology and levels of work engagement (see Table 2).

[Table 2 near here]

Network Estimation

The three networks estimated jointly for the three samples are visualized in Figure 1. The network density equaled .93 (42/45 edges) for Network 1, .89 (40/45 edges) for Network 2, and .87 (39/45 edges) for Network 3. The mean absolute edge weights equalled .11, .10, and .10 for Network 1, Network 2, and Network 3, respectively. The spin-glass algorithm identified the same three clusters in the three networks. The first cluster included Salience (1), Mood modification (3), and Withdrawal (5). The second cluster included Tolerance (2), Relapse (4), Conflict (6), and Problems (7). The third cluster included Vigor (V), Dedication (D), and Absorption (A). The cluster of work engagement was connected with the clusters of work addiction by several consistent edges (see Figure 1). The strongest positive edges were Withdrawal (5)—Absorption (A), Mood modification (3)—Absorption (A), and Salience (1)—Absorption (A). The strongest negative edges were Mood modification (3)—Dedication (D), Problems (7)—Vigor (V), and Conflict (6)—Vigor (V).

[Figure 1 near here]

Network Stability

Stability analyses showed that all three networks were accurately estimated, with small to moderate confidence intervals around the edge weights. The correlation stability coefficients exceeded the minimal threshold of .25 for stable estimation of centrality indices (Epskamp et al., 2018) for Network 2 (.44) and did not exceed this threshold for Network 1 (.21) and Network 3 (.13). Consequently, we focused on a detailed interpretation of the standard version of the node strength only in Network 2.

Network Inference

In the case of Network 2, Dedication (D) was the most central node (unstandardized value equalled 1.20), and Salience (1) was the least central node (unstandardized value equalled 0.80). However, the standard version of the node strength poorly differentiated node centrality in the three networks (see panel A on Figure 2). Spearman correlation coefficients of the standard version of the node strength equalled .82 for Network 1 and Network 2, .88 for Network 1 and Network 3, and .62 for Network 2 and Network 3.

[Figure 2 near here]

The bridge strength showed that Mood modification (3) was the most central symptom of work addiction (unstandardized value equalled 0.22 for Network 1, 0.27 for Network 2, and 0.20 for Network 3) and that Absorption (A) was the most central dimension of work engagement (unstandardized value equalled 0.42 for Network 1, 0.35 for Network 2, and 0.45 for Network 3; see panel B on Figure 2). Spearman correlation coefficients of the bridge strength equalled .95 for Network 1 and Network 2, .89 for Network 1 and Network 3, and .87 for Network 2 and Network 3.

Predictability analysis showed that Conflict (6) was the most predictable symptom of work addiction (average predictability equalled 22.7%) and that Mood modification (3) was the least predictable symptom of work addiction (average predictability equalled 8.4%; see Figure 1). The three dimensions of work engagement showed a similarly high level of predictability, and Dedication (D) was the most predictable one (average predictability equalled 66.2%). Average predictability equalled 36.9% in Network 1, 37.1% in Network 2, and 38.6% in Network 3.

Network Comparison

Spearman correlation coefficients of edge weights equalled .95 for Network 1 and Network 2, .95 for Network 1 and Network 3, and .94 for Network 2 and Network 3. In the omnibus tests of the

three possible pairwise comparisons, Network 1 differed significantly from Network 2 ($p = .032$), Network 1 differed significantly from Network 3 ($p = .042$), and Network 2 did not differ significantly from Network 3 ($p = .124$). The comparison of Network 1 and Network 2 revealed that of all 45 edges, seven edges (15.6%) differed significantly: Relapse (4)—Withdrawal (5), Salience (1)—Conflict (6), Relapse (4)—Conflict (6), Problems (7)—Vigor (V), Tolerance (2)—Dedication (D), Vigor (V)—Dedication (V), Withdrawal (5)—Absorption (A). The comparison of Network 1 and Network 3 revealed that of all 45 edges, three edges (6.7%) differed significantly: Mood modification (3)—Withdrawal (5), Withdrawal (5)—Conflict (6), and Vigor (V)—Dedication (D). Global strength did not differ significantly ($p > .05$) between the three networks, and its values were 4.61, 4.58, and 4.66 for Network 1, Network 2, and Network 3, respectively.

Figure 3 depicts the cross-sample network with averaged edge weights (panel A), the cross-sample variability network (panel B), the unstandardized values of the standard version of the node strength in the cross-sample network (panel C), and the unstandardized values of the bridge strength in the cross-sample network (panel D). The strongest edges connecting the seven symptoms of work addiction and the three dimensions of work engagement were Withdrawal (5)—Absorption (A), Mood modification (3)—Absorption (A), and Mood modification (3)—Dedication (D) with edge weights of .10, .10, and $-.10$, respectively. The most variable edges connecting the seven symptoms of work addiction and the three dimensions of work engagement were Problems (7)—Vigor (V), Mood modification (3)—Dedication (D), and Withdrawal (5)—Absorption (A), with standard deviations of .06, .05, and .05, respectively.

[Figure 3 near here]

The correlation stability coefficient of the cross-sample network was equal to .52 and exceeded the recommended threshold of .50 for stable estimation of centrality indices (Epskamp et al., 2018).

The standard version of the node strength showed that Relapse (4) was the most central symptom of work addiction (unstandardized value equalled 1.03), Salience (1) was the least central symptom of work addiction (unstandardized value equalled 0.75), and Dedication (D) was the most central dimension of work engagement (unstandardized value equalled 1.11). The bridge strength showed that Mood modification (3) was the most central symptom of work addiction (unstandardized value equalled 0.26), Relapse (4) was the least central symptom of work addiction (unstandardized value equalled 0.00), and Absorption (A) was the most central dimension of work engagement (unstandardized value equalled 0.39).

Discussion

This study aimed to investigate direct relationships of work addiction symptoms with work engagement dimensions in the three samples with diverse cultural and sociodemographic backgrounds. For this purpose, we jointly estimated the three networks from the three samples and combined the three samples into one to estimate the cross-sample network; the edges estimated in those networks were stable. There were a few differences in edge weights between the networks (two related to edges between work engagement dimensions and work addiction symptoms). The dissimilarities occurred between Polish and Norwegian networks, whereas there were none between the two Polish networks. They might indicate some cultural differences in the mechanisms of work engagement and its relationship to work addiction in Poland and Norway (see Schaufeli, 2017). Still, we see no consistent pattern of those differences, and the presented results do not allow us to draw any sensible conclusions on the nature of those differences.

In the estimated networks, we observed three distinct clusters of nodes; one cluster for the dimensions of work engagement and two clusters for the work addiction symptoms (Hypothesis 1 substantiated). The work engagement cluster was connected to the work addiction clusters through the

negative edges between Vigor (V) and Mood modification (3), Conflict (6), and Problems (7) and positive edges between Absorption (A) and all the addiction symptoms (however, Absorption [A] formed the most stable relationships with Salience [1], Tolerance [2], Mood modification [3], Withdrawal [5], and Conflict [6]). Moreover, the work engagement cluster was connected to the work addiction clusters through the positive edge between Dedication (D) and Tolerance (2), and the negative edge between Dedication (D) and Mood modification (3; see Figure 1 and Figure 3; Hypothesis 2 partially substantiated). These results indicate that lower energy (vigor) in work co-occurs with a tendency to improve one's mood through work, work-related internal and external conflicts, and work-related problems. Moreover, higher work absorption co-occurs with experiencing all addiction symptoms, and higher work dedication co-occurs with staying longer hours at work and less frequent mood modifying through work. The engagement cluster showed stronger connection with the cluster including salience, mood modification, and withdrawal than with the cluster including tolerance, relapse, conflict, and problems. This disproportion in number and strength of the edges between the two pairs of clusters provides additional supports for the assumption that the two clusters represent groups of more and less pathological symptoms of work addiction (Bereznowski et al., 2021; see also Charlton & Danforth, 2007).

The observed number of the edges connecting the work engagement cluster with the work addiction clusters substantially surpassed the number we expected and hypothesized. Nevertheless, all of the edges were weak (in most cases, their absolute values were smaller than or equal to .10), which is consistent with previous studies of the relationship between work addiction and work engagement (Clark et al., 2016; Di Stefano & Gaudiino, 2019). The unexpected edges could indicate that the presence of symptoms of work addiction deteriorates work engagement of working individuals (e.g., an

individual who uses work for mood modification becomes less dedicated and has less energy to work overtime), which would be compatible with the network theory of mental disorders (Borsboom, 2017).

The correlation stability coefficient indicated that the standard version of the node strength was not stable in two of the three jointly estimated networks. For this reason, we have established the bridge strength, which includes only the edges between the engagement and addiction clusters. We reckon that this solution may be better when the bridges do not result from overlapping symptoms (e.g., as in the case of depression and anxiety; see Borsboom & Cramer, 2013). Based on the bridge strength, we found that Absorption (A) had the strongest and direct connections with addiction symptoms and Mood modification (3) had the strongest and direct relations with the dimension of work engagement (see Figure 2; Hypothesis 3 substantiated). These results suggest that highly engaged employees can develop addiction through excessive absorption with work when they neglect other spheres of life. Mood modification could be the first symptom that prognoses future work addiction development. It is consistent with the theory of addiction that conceptualizes the disorder as a maladaptive form of modifying one's mood (Shaffer et al., 2004; see also Jacobs, 1986). However, the sole positive influence of working on one's emotional state must not be necessarily equal to being addicted (Griffiths et al., 2018).

Moreover, it has to be acknowledged that work may improve mood in numerous non-pathological ways. Like other substances and behaviors, it can be a potent but safe mood enhancer when used in moderation. It is strictly related to the ability of work to give rush and "high" (see Robinson, 2014). This experience is also a definitional part of the absorption component of engagement. However, when it starts to be used habitually and gets out of control, addiction may develop. According to our results, the highly engaged employees might use excessive work to cope with various difficulties and escape negative emotions. On the other hand, connections between

absorption and addiction symptoms could be attributed to content validity issues of the work addiction items (Bereznowski et al., 2021, Bereznowski & Konarski, 2020; see also Kulikowski, 2019). Some of work addiction items may not capture the clinical addictive aspect of excessive work involvement fully. In that case, apart from work addiction, those items can also measure engagement and, specifically, absorption. However, separating "high" and flow characterized by absorption present in healthy engagement and addiction may be psychometrically very complex. By analogy, many effects of alcohol intoxication are indistinguishable in individuals addicted to alcohol and non-problematic alcohol consumers, e.g., decreased fear or tension. Consequently, more studies examining the validity of both addiction and engagement are needed to understand this issue fully. Perhaps, the only way to control the shared components of absorption in engagement and addiction in practice is through analytical, statistical procedures (Atroszko & Atroszko, 2019).

In general, the predictability in all three networks was comparable. The most predictable node for the addiction cluster was Conflict (6), while the least predictable was Mood modification (3). The predictability was similar for all the dimensions in work engagement, but Dedication (D) was the most predictable. These results imply that among work addiction symptoms, internal and external conflicts related to addiction might be the most easily diminished through interventions aimed at different symptoms of work addiction and dimensions of work engagement. However, the inclusion of the dimensions of work engagement in the networks only slightly increased the predictability of work addiction symptoms in comparison to networks including only the symptoms (Bereznowski et al., 2021), which indicates that the development of work addiction purely based on high work engagement is unlikely. Moreover, these results imply that work engagement dimensions strongly predict each other. Work engagement might be a system that is easier to change as a whole rather than through several localized interventions focused at a single dimension or that work engagement is better

conceptualized in the latent trait framework than in the network framework (Golino & Epskamp, 2017; see also Kulikowski, 2019).

Strengths and Limitations

The investigation was performed in three large samples that differed in terms of nationality and sociodemographic background. The networks were estimated using joint network estimation and compared quantitatively. Work addiction and work engagement were measured with the same instrument (i.e., the BWAS and the UWES) in each sample. The dimensions of work engagement were measured with three items each, which should reduce bias related to the unreliability of single-item indicators. The three networks estimated in this study included the external field of work addiction symptoms (i.e., the dimensions of work engagement; Borsboom, 2017), which addresses the issue of rare investigation of external fields of mental disorders in psychological networks (Fried, 2020). As a result, this study contributes not only to the literature on compulsive overworking and behavioral addictions but also to the still scant literature on the replicability of psychological networks (Borsboom et al., 2017; Forbes et al., 2017a, 2017b) and literature on the external fields of mental disorders.

In terms of limitations, the three samples were predominantly female. They represented general populations from just two European countries, which puts restrictions on the generalizability of the results to clinical populations and populations from other countries and cultures. The data were cross-sectional, which puts limitations on causal inference. The symptoms of work addiction were measured with single items, which may bias estimates of network parameters. The estimated networks might include a few spurious edges connecting the engagement cluster and the addiction clusters as the power of jointly estimated networks has not been thoroughly studied yet. Last but not least, this study did not account for the effects of other mental disorders and psychological constructs (e.g., occupational stress

and job burnout; Clark et al., 2016), which may influence the direct relationships between work addiction symptoms and work engagement dimensions.

Conclusions and Future Studies Directions

This study showed that absorption is directly positively related to all symptoms of work addiction, vigor is directly negatively related to mood modification, conflict, and problems, and dedication is directly positively related to tolerance and directly negatively related to mood modification. There were two most important results related to the relationship between work addiction and work engagement. First, absorption showed multiple direct relationships with work addiction symptoms. Second, mood modification showed multiple direct relationships with work engagement dimensions. These results suggest that further investigation of properties of absorption and mood modification might be crucial for answering the question of how engaged workers become addicted to work. At the same time, the results show that network analysis might be a useful analytical technique for untangling some complicated relationships between psychological phenomena.

Future studies should investigate networks including additional variables in the external field of the work addiction symptoms such as job burnout, occupational stress, perfectionism, or work-life conflict (see Clark et al., 2016). Cross-validation of the investigated networks with different item wordings would increase the generalizability of the results and perhaps improve the validity of networks. Also, studies based on clinical samples and epidemiological surveys, including other psychopathologies and studies investigating potential sex differences in networks, are highly warranted. These should include replication of the current study on study addiction conceptualized as an early form of work addiction (Atroszko et al., 2015, 2016) and intensive longitudinal designs, which would allow investigating the assumption that cross-sectional data is a good representation of a dynamic process of work addiction within individuals. Moreover, future studies should investigate the

direction of the relationships between work addiction symptoms and work engagement dimensions using structural equation modelling. Last but not least, future studies should investigate the properties of the bridge strength index introduced in this study.

References

- Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy white women. *Health Psychology, 19*(6), 586–592. <https://doi.org/10.1037/0278-6133.19.6.586>
- Andreassen, C. S., Griffiths, M. D., Hetland, J., Kravina, L., Jensen, F., & Pallesen, S. (2014). The prevalence of workaholism: A survey study in a nationally representative sample of Norwegian employees. *PLoS ONE, 9*(8), 1–10. <https://doi.org/10.1371/journal.pone.0102446>
- Andreassen, C. S., Griffiths, M. D., Hetland, J., & Pallesen, S. (2012). Development of a work addiction scale. *Scandinavian Journal of Psychology, 53*(3), 265–272. <https://doi.org/10.1111/j.1467-9450.2012.00947.x>
- Andreassen, C. S., Griffiths, M. D., Sinha, R., Hetland, J., & Pallesen, S. (2016). The relationships between workaholism and symptoms of psychiatric disorders: A large-scale cross-sectional study. *PLoS ONE, 11*(5), 1–19. <https://doi.org/10.1371/journal.pone.0152978>
- Andreassen, C. S., Nielsen, M. B., Pallesen, S., & Gjerstad, J. (2019). The relationship between psychosocial work variables and workaholism: Findings from a nationally representative survey. *International Journal of Stress Management, 26*(1), 1–10. <https://doi.org/10.1037/str0000073>
- Andreassen, C. S., Schaufeli, W. B., & Pallesen, S. (2018). Myths about "The myths about work addiction". Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions, 7*(4), 858–862. <https://doi.org/10.1556/2006.7.2018.126>
- Atroszko, P. A., Andreassen, C. S., Griffiths, M. D., & Pallesen, S. (2015). Study addiction—A new area of psychological study: Conceptualization, assessment, and preliminary empirical findings.

Journal of Behavioral Addictions, 4(2), 75–84. <https://doi.org/10.1556/2006.4.2015.007>

Atroszko, P. A., Andreassen, C. S., Griffiths, M. D., & Pallesen, S. (2016). The relationship between study addiction and work addiction: A cross-cultural longitudinal study. *Journal of Behavioral Addictions*, 5(4), 708–714. <https://doi.org/10.1556/2006.5.2016.076>

Atroszko, P. A., & Atroszko, B. (2019). Type-A personality competitiveness component linked to increased cardiovascular risk is positively related to study addiction but not to study engagement. *Current Science*, 117(7), 1184–1188. <https://doi.org/10.18520/cs/v117/i7/1184-1188>

Atroszko, P. A., Demetrovics, Z., & Griffiths, M. D. (2019). Beyond the myths about work addiction: Toward a consensus on definition and trajectories for future studies on problematic overworking. A response to the commentaries on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 8(1), 7–15. <https://doi.org/10.1556/2006.8.2019.11>

Atroszko, P. A., Pallesen, S., Griffiths, M. D., & Andreassen, C. S. (2017). Work addiction in Poland: Adaptation of the Bergen Work Addiction Scale and relationship with psychopathology. *Health Psychology Report*, 5(4), 345–355. <https://doi.org/10.5114/hpr.2017.68759>

Bailey, C., Madden, A., Alfes, K., & Fletcher, L. (2017). The meaning, antecedents and outcomes of employee engagement: A narrative synthesis. *International Journal of Management Reviews*, 19(1), 31–53. <https://doi.org/10.1111/ijmr.12077>

Bereznowski, P., & Konarski, R. (2020). Is the polythetic approach efficient in identifying potentially addicted to work individuals? Comparison of the polythetic approach with the item response theory framework. *Polish Psychological Bulletin*, 51(2), 98–115. <https://doi.org/10.24425/ppb.2020.133768>

Bereznowski, P., Atroszko, P. A., & Konarski, R. (2021). *Network approach to work addiction: A cross-cultural study showed a high replicability of networks across samples from different countries*

and of diverse sociodemographic backgrounds. PsyArXiv.

<https://doi.org/10.31234/osf.io/dy92g>

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry, 16*(1), 5–13.

<https://doi.org/10.1002/wps.20375>

Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*, 91–121.

<https://doi.org/10.1146/annurev-clinpsy-050212-185608>

Borsboom, D., Fried, E. I., Epskamp, S., Waldorp, L. J., van Borkulo, C. D., van der Maas, H. L. J., & Cramer, A. O. J. (2017). False alarm? A comprehensive reanalysis of "Evidence that psychopathology symptom networks have limited replicability" by Forbes, Wright, Markon, and Krueger (2017). *Journal of Abnormal Psychology, 126*(7), 989–999.

<https://doi.org/10.1037/abn0000306>

Brown, R. I. F. (1993). Some contributions of the study of gambling to the study of other addictions. In W. R. Eadington & J. A. Cornelius (Eds.), *Gambling behaviour and problem gambling* (pp. 241–272). Reno, NV: University of Nevada.

Burger, J., Isvoranu, A. M., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., Fried, E. I., Borsboom, D., & Blanken, T. F. (2020). *Reporting standards for psychological network analyses in cross-sectional data.* PsyArXiv. <https://doi.org/10.31234/osf.io/4y9nz>

Charlton, J. P., & Danforth, I. D. W. (2007). Distinguishing addiction and high engagement in the context of online game playing. *Computers in Human Behavior, 23*(3), 1531–1548.

<https://doi.org/10.1016/j.chb.2005.07.002>

Clark, M. A., Michel, J. S., Zhdanova, L., Pui, S. Y., & Baltes, B. B. (2016). All work and no play? A meta-analytic examination of the correlates and outcomes of workaholism. *Journal of*

Management, 42(7), 1836–1873. <https://doi.org/10.1177/0149206314522301>

Clark, M. A., Smith, R. W., & Haynes, N. J. (2020). The Multidimensional Workaholism Scale:

Linking the conceptualization and measurement of workaholism. *Journal of Applied Psychology*, 105(11), 1281–1307. <https://doi.org/10.1037/apl0000484>

Contreras, A., Nieto, I., Valiente, C., Espinosa, R., & Vazquez, C. (2019). The study of

psychopathology from the network analysis perspective: A systematic review. *Psychotherapy and Psychosomatics*, 88(2), 71–83. <https://doi.org/10.1159/000497425>

Costantini, G., & Epskamp, S. (2017). EstimateGroupNetwork: Perform the joint graphical lasso and

select tuning parameters. R package (Version 0.3.1) [Computer software]. Retrieved from <https://cran.r-project.org/web/packages/EstimateGroupNetwork/index.html>

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research.

InterJournal, 1–9.

Di Stefano, G., & Gaudiino, M. (2019). Workaholism and work engagement: How are they similar?

How are they different? A systematic review and meta-analysis. *European Journal of Work and Organizational Psychology*, 28(3), 329–347. <https://doi.org/10.1080/1359432X.2019.1590337>

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their

accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195–212.
<https://doi.org/10.3758/s13428-017-0862-1>

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph:

Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, 48(4), 1–18. <https://doi.org/10.18637/jss.v048.i04>

- Forbes, M. K., Wright, A. G. C., Markon, K. E., & Krueger, R. F. (2017a). Evidence that psychopathology symptom networks have limited replicability. *Journal of Abnormal Psychology, 126*(7), 969–988. <https://doi.org/10.1037/abn0000276>
- Forbes, M. K., Wright, A. G. C., Markon, K. E., & Krueger, R. F. (2017b). Further evidence that psychopathology networks have limited replicability and utility: Response to Borsboom et al. (2017) and Steinley et al. (2017). *Journal of Abnormal Psychology, 126*(7), 1011–1016. <https://doi.org/10.1037/abn0000313>
- Fried, E. I. (2017). The 52 symptoms of major depression: Lack of content overlap among seven common depression scales. *Journal of Affective Disorders, 208*, 191–197. <https://doi.org/10.1016/j.jad.2016.10.019>
- Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry, 31*(4), 271–288. <https://doi.org/10.1080/1047840X.2020.1853461>
- Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., Huisman-van Dijk, H. M., Bockting, C. L. H., Engelhard, I., Armour, C., Nielsen, A. B. S., & Karstoft, K. I. (2018). Replicability and generalizability of posttraumatic stress disorder (PTSD) networks: A cross-cultural multisite study of PTSD symptoms in four trauma patient samples. *Clinical Psychological Science, 6*(3), 335–351. <https://doi.org/10.1177/2167702617745092>
- Fried, E. I., van Borkulo, C. D., Cramer, A. O. J., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology, 52*(1), 1–10. <https://doi.org/10.1007/s00127-016-1319-z>

- Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE*, 12(6), 1–26.
<https://doi.org/10.1371/journal.pone.0174035>
- Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, 10(4), 191–197. <https://doi.org/10.1080/14659890500114359>
- Griffiths, M. (2011). Workaholism—A 21st-century addiction. *The Psychologist: Bulletin of the British Psychological Society*, 24(10), 740–744.
- Griffiths, M. D., Demetrovics, Z., & Atroszko, P. A. (2018). Ten myths about work addiction. *Journal of Behavioral Addictions*, 7(4), 845–857. <https://doi.org/10.1556/2006.7.2018.05>
- Haslbeck, J. (2019). mgm: Estimating time-varying k-order mixed graphical models. R package (Version 1.2-11) [Computer software]. Retrieved from <https://cran.r-project.org/web/packages/mgm/index.html>
- Haslbeck, J. M. B., & Waldorp, L. J. (2018). How well do network models predict observations? On the importance of predictability in network models. *Behavior Research Methods*, 50(2), 853–861. <https://doi.org/10.3758/s13428-017-0910-x>
- Jacobs, D. F. (1986). A general theory of addictions: A new theoretical model. *Journal of Gambling Behavior*, 2(1), 15–31. <https://doi.org/10.1007/BF01019931>
- Khazaal, Y., Breivik, K., Billieux, J., Zullino, D., Thorens, G., Achab, S., ... Chatton, A. (2018). Gaming Addiction Scale assessment through a nationally representative sample of young adult man: Item response theory graded-response modeling. *Journal of Medical Internet Research*, 20(8), 1–16. <https://doi.org/10.2196/10058>
- Kulikowski, K. (2019). One, two or three dimensions of work engagement? Testing the factorial validity of the Utrecht Work Engagement Scale on a sample of Polish employees. *International*

Journal of Occupational Safety and Ergonomics, 25(2), 241–249.

<https://doi.org/10.1080/10803548.2017.1371958>

Kun, B. (2018). Ten myths and twenty years: What we know and what we still do not know about work addiction. Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 863–866. <https://doi.org/10.1556/2006.7.2018.125>

Leshner, A. I. (1997). Addiction is a brain disease, and it matters. *Science*, 278(5335), 45–47. <https://doi.org/10.1126/science.278.5335.45>

Lior, O., Abira, R., & Aviv, W. (2018). Work addiction: An organizational behavior as well as an addictive behavior? Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 888–891. <https://doi.org/10.1556/2006.7.2018.119>

Loscalzo, Y., & Giannini, M. (2018). Response to: Theoretical and methodological issues in the research on study addiction with relevance to the debate on conceptualising behavioural addictions: Atroszko (2018). *Psychiatria i Psychologia Kliniczna*, 18(4), 426–430. <https://doi.org/10.15557/PiPK.2018.0051>

Malgaroli, M., Calderon, A., & Bonanno, G. A. (2021). Networks of major depressive disorder: A systematic review. *Clinical Psychology Review*, 85, 1–14. <https://doi.org/10.1016/j.cpr.2021.102000>

Malinowska, D. (2018). How to counter the ten myths about work addiction?: Three postulates for future research. Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 871–874. <https://doi.org/10.1556/2006.7.2018.123>

Nerstad, C. G., Richardsen, A. M., & Martinussen, M. (2010). Factorial validity of the Utrecht Work Engagement Scale (UWES) across occupational groups in Norway. *Scandinavian Journal of Psychology*, 51(4), 326–333. <https://doi.org/10.1111/j.1467-9450.2009.00770.x>

- Operario, D., Adler, N. E., & Williams, D. R. (2004). Subjective social status: Reliability and predictive utility for global health. *Psychology & Health*, 19(2), 237–246.
<https://doi.org/10.1080/08870440310001638098>
- Quinones, C. (2018). Moving from the terminology debate to transdisciplinary understanding of the problem. Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 880–883. <https://doi.org/10.1556/2006.7.2018.121>
- R Core Team. (2021). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Robinaugh, D. J., Hoekstra, R. H. A., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine*, 50(3), 353–366. <https://doi.org/10.1017/S0033291719003404>
- Robinson, B. E. (2014). *Chained to the desk: A guidebook for workaholics, their partners and children, and the clinicians who treat them*. New York, NY: New York University Press.
- Rodebaugh, T. L., Tonge, N. A., Piccirillo, M. L., Fried, E., Horenstein, A., Morrison, A. S., Goldin, P., Gross, J. J., Lim, M. H., Fernandez, K. C., Blanco, C., Schneier, F. R., Bogdan, R., Thompson, R. J., & Heimberg, R. G. (2018). Does centrality in a cross-sectional network suggest intervention targets for social anxiety disorder? *Journal of Consulting and Clinical Psychology*, 86(10), 831–844. <https://doi.org/10.1037/ccp0000336>
- Schaufeli, W. B. (2017). Work engagement in Europe: Relations with national economy, governance and culture. *Organizational Dynamics*, 47(2), 99–106.
<https://doi.org/10.1016/j.orgdyn.2018.01.003>
- Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement*, 66(4), 701–716. <https://doi.org/10.1177/0013164405282471>

- Schaufeli, W. B., Salanova, M., González-romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, 3(1), 71–92. <https://doi.org/10.1023/A:1015630930326>
- Shaffer, H. J., LaPlante, D. A., LaBrie, R. A., Kidman, R. C., Donato, A. N., & Stanton, M. V. (2004). Toward a syndrome model of addiction: Multiple expressions, common etiology. *Harvard Review of Psychiatry*, 12(6), 367–374. <https://doi.org/10.1080/10673220490905705>
- Snir, R., & Harpaz, I. (2012). Beyond workaholism: Towards a general model of heavy work investment. *Human Resource Management Review*, 22(3), 232–243. <https://doi.org/10.1016/j.hrmr.2011.11.011>
- Sussman, S. (2018). Ten myths (of facts?) about workaholism: An appetitive motivation framework. Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 884–887. <https://doi.org/10.1556/2006.7.2018.120>
- Tóth-Király, I., Bőthe, B., & Orosz, G. (2018). Seeing the forest through different trees: A social psychological perspective of work addiction. Commentary on: Ten myths about work addiction (Griffiths et al., 2018). *Journal of Behavioral Addictions*, 7(4), 875–879. <https://doi.org/10.1556/2006.7.2018.122>
- Vallerand, R. J., Paquet, Y., Philippe, F. L., & Charest, J. (2010). On the role of passion for work in burnout: A process model. *Journal of Personality*, 78(1), 289–312. <https://doi.org/10.1111/j.1467-6494.2009.00616.x>
- van Borkulo, C., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Brosboom, D., Waldorp, L. J. (2017). *Comparing network structures on three aspects: A permutation test*. Unpublished manuscript. <https://doi.org/10.13140/RG.2.2.29455.38569>

Table 1

Sociodemographic Characteristics of the Three Samples

	Sample 1	Sample 2	Sample 3	Test of differences between samples
Description	Recent graduates	General population	Recent graduates	
Nationality	Norwegian	Polish	Polish	
<i>N</i>	755	701	697	
Sex				$\chi^2(2) = 26.64, p < .001$
Female	536 (71.0%)	495 (70.6%)	569 (81.6%)	
Male	219 (29.0%)	196 (28.0%)	128 (18.4%)	
No answer	0 (0.0%)	10 (1.4%)	0 (0.0%)	
Age (<i>M</i> [<i>SD</i>])	29.77 (7.15)	36.24 (11.30)	25.58 (3.41)	$F(2, 2142) = 318.8, p < .001$
Age (range)	21–61	20–79	22–51	
Marital status				$\chi^2(2) = 15.05, p < .001$

.001

In a relationship	560 (74.2%)	552 (78.7%)	489 (70.2%)
Not in a relationship	195 (25.8%)	145 (20.7%)	208 (29.8%)
No answer	0 (0.0%)	4 (0.6%)	0 (0.0%)

Number of children $\chi^2(8) = 366.44, p < .001$

0	552 (73.1%)	288 (41.1%)	631 (90.5%)
1	80 (10.6%)	154 (22.0%)	51 (7.3%)
2	76 (10.1%)	156 (22.3%)	15 (2.2%)
3	29 (3.8%)	32 (4.6%)	0 (0.0%)
4 or more	18 (2.4%)	14 (2.0%)	0 (0.0%)
No answer	0 (0.0%)	57 (8.1%)	0 (0.0%)

Highest completed education $\chi^2(3) = 86.04, p < .001$

Primary school	0 (0.0%)	NA	0 (0.0%)
----------------	----------	----	----------

Vocational school	0 (0.0%)	NA	0 (0.0%)	
High school	29 (3.8%) ^a	NA	0 (0.0%)	
Bachelor's degree	437 (57.9%)	NA	279 (40.0%) ^b	
Master's degree	287 (38.0%)	NA	412 (59.1%)	
PhD	2 (0.3%)	NA	6 (0.9%)	
Working hours per week (<i>M</i> [<i>SD</i>])	37.48 (7.24)	45.61 (11.75)	39.69 (10.26)	$F(2, 2130) = 129.53, p < .001$
Working hours per week (Range)	8–72	4–98	2–85	
Work status				$\chi^2(2) = 25.19, p < .001$
Full-time worker	629 (83.3%)	625 (89.2%)	580 (83.2%)	
Part-time worker	126 (16.7%)	59 (8.4%)	117 (16.8%)	
No answer	0 (0.0%)	17 (2.4%)	0 (0.0%)	
Gross income (categories) ^{cd}				

Category 1 (C1)	15 (2.0%)	81 (11.6%)	82 (11.8%)
Category 2 (C2)	58 (7.7%)	115 (16.4%)	285 (40.9%)
Category 3 (C3)	317 (42.0%)	120 (17.1%)	197 (28.3%)
Category 4 (C4)	304 (40.3%)	76 (10.8%)	67 (9.6%)
Category 5 (C5)	39 (5.2%)	61 (8.7%)	24 (3.4%)
Category 6 (C6)	14 (1.9%)	24 (3.4%)	21 (3.0%)
Category 7 (C7)	1 (0.1%)	4 (0.6%)	7 (1.0%)
Category 8 (C8)	2 (0.3%)	8 (1.1%)	4 (0.6%)
Category 9 (C9)	0 (0.0%)	6 (0.9%)	0 (0.0%)
Category 10 (C10)	0 (0.0%)	2 (0.3%)	1 (0.1%)
Category 11 (C11)	0 (0.0%)	4 (0.6%)	4 (0.6%)
No Answer	5 (0.7%)	200 (28.5%)	5 (0.7%)
Gross income (<i>M</i> [<i>SD</i>]) ^c	NA	46 029.08 (33 104.21) PLN	NA

Gross income (range) ^c	NA	0–200 000 PLN	NA	
Subjective socioeconomic status (<i>M [SD]</i>)	4.74 (1.37)	NA	5.28 (1.43)	$t(1447) = -7.29, p < 0.001$
Gathered	In October and November of 2016	From January 2014 to July 2016	In October 2016	
Symptom severity (<i>M [SD]</i>)	2.12 (0.75)	2.48 (0.83)	2.27 (0.80)	
Work engagement (<i>M [SD]</i>)	15.30 (3.51)	14.50 (3.86)	14.10 (3.65)	
More details in	Atroszko et al., 2016	Atroszko et al., 2017	Atroszko et al., 2016	

^aThese individuals declared that their highest completed level of education is a one year programme at a university (i.e., Årsenhet in Norwegian; this level of education is incomparable with categories in other studies), therefore we classified all of them as individuals whose highest completed level of education is high school. ^bSeventeen individuals declared that their highest completed level of education is some kind of postgraduate studies which can be completed both after Bachelor's degree and Master's degree (this level of education is incomparable with categories in other studies), therefore we classified all of them as individuals whose highest completed level of education is Bachelor's degree. ^cPast year personal annual income before tax in Norwegian and Polish currencies (i.e., NOK

and PLN). ^dCategories for gross income varied between samples. In Sample 1: C1 = 0–150 000 NOK, C2 = 150 001–300 000 NOK, C3 = 300 001–450 000 NOK, C4 = 450 001–600 000 NOK, C5 = 600 001–750 000 NOK, C6 = 750 001–900 000 NOK, C7 = 900 001–1 050 000 NOK, C8 = 1 050 001–1 200 000 NOK, C9 = 1 200 001–1 350 000 NOK, C10 = 1 350 001–1 500 000 NOK, C11 = 1 500 001 or more. In Sample 2 the open response on gross income was recoded to match categories in Sample 3. In Sample 3: C1 = 0–17 000 PLN, C2 = 17 001–34 000 PLN, C3 = 34 001–51 000 PLN, C4 = 51 001–68 000 PLN, C5 = 68 001–85 000 PLN, C6 = 85 001–102 000 PLN, C7 = 102 001–119 000 PLN, C8 = 119 001–136 000 PLN, C9 = 136 001–153 000 PLN, C10 = 153 001–170 000 PLN, C11 = 170 000 PLN or more.

Table 2

Overview of the Seven Symptoms of Work Addiction and the Three Dimensions of Work Engagement

No.	Node	Skewness (Kurtosis)			<i>M (SD)</i>			Test of differences between samples
		Sample 1	Sample 2	Sample 3	Sample 1	Sample 2	Sample 3	
1	Salience	0.69 (2.59)	0.14 (2.04)	0.44 (2.29)	2.00 (0.99)	2.54 (1.13)	2.19 (1.01)	$F(2, 2150) = 50.61, p < 0.001$
2	Tolerance	-0.01 (2.25)	-0.33 (2.33)	-0.10 (2.21)	2.74 (1.05)	3.18 (1.04)	2.86 (1.04)	$F(2, 2150) = 34.81, p < 0.001$
3	Mood modification	1.49 (4.44)	0.58 (2.18)	0.96 (2.92)	1.59 (0.91)	2.19 (1.19)	1.93 (1.08)	$F(2, 2150) = 57.70, p < 0.001$

								0.001
4	Relapse	1.16 (3.47)	0.42 (2.05)	0.82 (2.53)	1.78 (1.02)	2.37 (1.21)	2.07 (1.19)	$F(2, 2150) =$ 48.46, $p <$ 0.001
5	Withdrawal	0.47 (2.25)	0.58 (2.40)	0.78 (2.78)	2.24 (1.11)	2.24 (1.16)	1.99 (1.04)	$F(2, 2150) =$ 11.60, $p <$ 0.001
6	Conflict	0.18 (2.20)	0.07 (1.89)	0.09 (1.96)	2.54 (1.12)	2.67 (1.23)	2.73 (1.23)	$F(2, 2150) =$ 4.65, $p = 0.010$
7	Problems	0.93 (3.09)	0.56 (2.16)	0.75 (2.51)	1.92 (1.03)	2.18 (1.16)	2.13 (1.18)	$F(2, 2150) =$ 10.66, $p <$ 0.001
8	Vigor	-0.74 (3.25)	-0.55 (2.51)	-0.31 (2.43)	15.40 (3.74)	14.32 (4.20)	13.50 (3.99)	$F(2, 2150) =$ 41.77, $p <$ 0.001

9	Dedication	−1.02 (3.87)	−0.57 (2.52)	−0.56 (2.45)	16.54 (3.72)	15.05 (4.42)	14.95 (4.17)	$F(2, 2150) =$ $34.79, p <$ 0.001
10	Absorption	−0.37 (2.57)	−0.48 (2.46)	−0.53 (2.54)	13.86 (4.19)	14.06 (4.51)	13.88 (4.23)	$F(2, 2150) =$ $0.46, p = 0.631$

Network 1

Network 2

Network 3

Figure 1. The three regularized partial correlation networks estimated jointly for the three samples. The lighter grey nodes represent the symptoms of work addiction and the darker grey nodes represent the dimensions of work engagement. Solid lines represent positive edges and dashed lines represent negative edges. Line thickness and darkness indicate the strength of a relationship. In the case of symptoms of work addiction, the lighter grey area in the ring around a node represents predictability based on the variance of a symptom explained by all of its neighbours and the darker grey area in the

ring around a node represent predictability based on the marginal distribution of a node. In the case of dimensions of work engagement, the black area in the ring around a node represents a proportion of explained variance (R^2). 1 = Salience; 2 = Tolerance; 3 = Mood modification; 4 = Relapse; 5 = Withdrawal; 6 = Conflict; 7 = Problems; V = Vigor; D = Dedication; A = Absorption.

Figure 2. Panel A shows the unstandardized values of the standard version of the node strength in the three networks. Panel B shows the unstandardized values of the bridge strength in the three networks.

Figure 3. Panel A shows the cross-sample network, which was obtained by pooling all observations into one sample, and panel B shows the cross-sample variability network in which edge weights represent the standard deviation of edge weights between the three jointly estimated networks. The lighter grey nodes represent the symptoms of work addiction, and the darker grey nodes represent the dimensions of work engagement. Solid lines represent positive edges, and dashed lines represent negative edges. Line thickness and darkness indicate the strength of a relationship. In the case of

symptoms of work addiction on panel A, the lighter grey area in the ring around a node represents predictability based on the variance of a symptom explained by all of its neighbours, and the darker grey area in the ring around a node represent predictability based on the marginal distribution of a node. In the case of dimensions of work engagement on panel A, the black area in the ring around a node represents a proportion of explained variance (R^2). Panel C shows the unstandardized values of the standard version of the node strength in the cross-sample network. Panel D shows the unstandardized values of the bridge strength in the cross-sample network.