Network Approach to Work Addiction: A Cross-Cultural Study

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Abstract

The network approach to psychopathology conceptualizes mental disorders as dynamic systems consisting of symptoms that are in direct relationships with each other. In this study, we aimed to estimate and compare networks of work addiction among Norwegian and Polish working individuals. We used four samples in which work addiction was measured with the Bergen Work Addiction Scale. Two samples comprised responses from working Norwegians ($n_1 = 16,426$; $n_2 = 764$) and two samples comprised responses from working Poles ($n_3 = 719$; $n_4 = 711$). We jointly estimated four networks using the fused graphic lasso method. Additionally, we estimated symptoms centrality, symptoms predictability, the stability of each network, and quantitatively compared all networks. The results showed highly similar networks across the four samples. There were several strong direct relationships between symptoms. The most and the least central symptoms were Relapse and Mood modification, respectively. Mean symptom predictability varied between 22.6% and 28.3% across samples. Issues of proper symptom measurement and understanding of strict interconnectedness of addiction symptoms in networks are discussed.

Keywords: network analysis, network approach, the Bergen Work Addiction Scale, work addiction, workaholism

Introduction

The network theory of mental disorders conceptualizes mental disorders as dynamic systems consisting of symptoms in direct relationships (Borsboom, 2017). In recent years, it has become a popular framework for studying mental disorders (Contreras et al., 2019; Robinaugh et al., 2020). In this study, we aimed to estimate and compare networks of work addiction among working Norwegians and Poles.

Work Addiction

A recent debate on the current status of work addiction gave rise to general agreements among leading experts, predominantly clinically oriented, researching in this field (Atroszko et al., 2019; see also Andreassen et al., 2018; Griffiths et al., 2018; Kun, 2018; Lior et al., 2018; Malinowska, 2018; Quinones, 2018; Sussman, 2018; Tóth-Király et al., 2018). All of the experts considered that compulsive overworking is a genuine problem and requires more high-quality studies. Currently, work addiction is being gradually, though still very slowly, recognized as a major epidemiological concern globally (Atroszko et al., 2020), and more systematic and integrated efforts to research work addiction are undertaken. It was suggested that, similar to other addictions, work addiction is strictly related to ineffective coping with other underlying problems and stress (Atroszko et al., 2019; Atroszko, 2019a, 2019b; Sussman, 2012).

Other conceptualizations of compulsive overworking are also proposed in the literature; however, they do not define this phenomenon within the addiction framework (e.g., Clark et al., 2020; Loscalzo & Giannini, 2018), and sometimes place it in more general frameworks of high engagement in work (Snir & Harpaz, 2012; Vallerand et al., 2010). The interpretation of network analysis is inseparably tied to operationalization and measurement of symptoms of work addiction (Fried, 2017; Malgaroli et al., 2021). Therefore, for clarity, in this paper, we describe only a common addiction components model (Brown, 1993; Griffiths, 2005), which was used for the development of instrument

measuring symptoms of work addiction applied in this study (the Bergen Work Addiction Scale; BWAS; Andreassen et al., 2012). Since work addiction is conceptualized as a potential addictive disorder and components model properly captures common symptomatology across addictions, the BWAS reflects valid operationalization of this phenomenon.

The common addiction components model developed by Brown (1993) and applied widely to behavioral addictions by Griffiths (2005) allowed for the rapid growth of behavioral addiction research due to its simplicity and universality (Griffiths, 2019). It is congruent with the syndrome model of addiction, postulating that all addictive behaviors share etiology and common manifestations, which is one of the most widely recognized general models of addiction (Shaffer et al., 2004). The common addiction components model, together with a simple screening instrument, was explicitly applied to work addiction in the last decade and enabled a more rigorous investigation of this addiction within the clinical framework in large-scale surveys and experiments. The model includes seven addiction symptoms.

Salience (1) refers to the constant preoccupation with work, which manifests itself in the dominance of work in thoughts, feelings, and behavior of the individual. *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, to the conflicts between the work and other activities such as social life and hobbies, and to the intrapsychic

conflicts such as incompatible needs. *Problems* (7) component refers to the health and/or other problems, which are the results of excessive working (Andreassen et al., 2012; Griffiths, 2011).

Previous studies showed that there are some non-trivial relationships between the symptoms of work addiction, which could not be explained by a single latent variable of work addiction (Atroszko et al., 2017; Bereznowski & Konarski, 2020; Lichtenstein et al., 2019; Orosz et al., 2016; cf. Andreassen et al., 2012). In this paper, we hypothesize that these relationships are the direct relationships between symptoms postulated by the network theory of mental disorders (Borsboom, 2017). This assumption seems to be congruent with a clinical practice in which intervention strategies focused on particular symptoms and relations between them, as in cognitive-behavioral therapy, are usually successful (Andreassen, 2014; Robinson, 2014). Therefore, the network approach to work addiction could constitute a bridge between the results of quantitative studies of work addiction and intervention strategies applied in the clinical practice.

Network Approach to Work Addiction

Based on the addiction framework, it can be assumed that the process of increasing involvement in a behavior that is central in one's life (salience) is related to the development of compulsion because it gradually serves more and more mood modification purposes, which, in turn, increases tolerance, withdrawal, and relapse and leads to negative consequences in the form of conflicts and problems (Shaffer et al., 2004). Taking into account feedback loops, it can be expected that increasing problems may increase mood modification needs and aggravate tolerance, withdrawal, and relapse symptoms. Taking these assumptions into account, we argue that work addiction could be conceptualized as a network of direct relationships between its symptoms. While acknowledging the necessity for a confirmatory approach in behavioral sciences (Wagenmakers et al., 2012), we argue that, in the case of a complex network of interrelationships, imposing specific predictions in the context of almost complete lack of previous reliable data and solid theories, it would be to a large extent arbitrary and

potentially highly confusing. At the same time, we plea for a confirmatory approach with subsequent investigations of this area of research and the development of robust models explaining the observed patterns.

Networks' Replicability and Cross-Cultural Differences

In this paper, we aimed not only to estimate a network of work addiction but also to investigate whether this network will replicate across samples of working individuals from different countries (Norway and Poland) and of diverse sociodemographic backgrounds. The most important work-related differences between Norway and Poland include, but are not limited to, gross domestic product (GDP) per capita, labour laws and social care regulations, and cultural differences (Hofstede et al., 2010). Taken together, these are reflected in considerable differences in the socioeconomic uncertainty between Norway and Poland, and these were found to affect work-related compulsive behaviors in previous studies in two countries (Atroszko & Atroszko, 2020; Atroszko & Pallesen, 2014; Atroszko et al., 2017). The young age and early stage of career of recent university graduates 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. These differences could lead to differences in patterns of work addiction and its networks (for an example of cross-cultural and age-related differences in work-related behaviors, see Hu et al., 2014; Kooij et al., 2010). However, previous studies showed a satisfactory level of replicability of networks, especially when the same measurement tool was used in each sample (Böthe et al., 2020; Fried et al., 2018; Hirota et al., 2020; Huang et al., 2020), even though the generalizability of such networks still has some limitations (Malgaroli et al., 2021). Consequently, we expect that four networks of work addiction estimated in this study would show a high level of replicability. Nevertheless, some differences are likely to be observed, and we

expect that the most considerable differences would be observed between samples, including individuals with simultaneously different nationalities and sociodemographic backgrounds.

Hypotheses

Based on previous empirical research and theoretical considerations, we formulated the following hypotheses. Hypothesis 1: Work addiction network would have a non-trivial topology, in which certain symptoms would be more tightly connected than others. Hypothesis 2: Work addiction networks would replicate across samples, including working individuals from different countries and of diverse sociodemographic backgrounds.

Method

Participants and Procedure

In this study, we used four samples from research with a focus on work addiction; two included responses of working Norwegians (Sample 1 and Sample 2), and two included responses of working Poles (Sample 3 and Sample 4). Two samples included the general working population (Sample 1 and Sample 3), and two samples included individuals of considerably younger age and different sociodemographics (Sample 2 and Sample 4). 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. Detailed characteristics of the four samples are presented in Table 1. Information about participants' compensation and deleted observations are presented in Supplemental Materials.

Measures

The 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 Sample 2, and the Polish version of the scale was used in Sample 3 and Sample 4. Both versions of the BWAS showed good content validity, convergent validity, and criterion validity in previous studies (Andreassen et al., 2012; Atroszko et al., 2017). The Cronbach's alpha reliability coefficients were .86 for Sample 1, .85 for Sample 2, .84 for Sample 3, and .85 for Sample 4.

In each sample, participants were asked about sex, age, marital status, work status, and gross income (i.e., past year personal annual income before tax). In the case of gross income, participants in Sample 1, Sample 2, and Sample 4 were asked a closed-ended question with different ranges of income for each category in each Sample (see Table 1), and participants in Sample 3 were asked an open-ended question about their last year's income. Additionally, participants in Sample 2, Sample 3, and Sample 4 were asked about the number of children and working hours per week, participants in Sample 1, Sample 2, and Sample 4 were asked about the highest completed level of education, and subjective socioeconomic status was measured in Sample 2 and Sample 4 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 used by Fried et al. (2018): (a) network estimation, (b) network inference, (c) network stability, and (d) network comparison. For reporting the results, we followed the reporting standards for psychological network analyses in cross-sectional data set by Burger et al. (2020). The

analytic code for all analyses performed in this study and the Supplemental Materials are available at <https://osf.io/76kpw>.

Network Estimation

To jointly estimate the four networks of work addiction, we used a fused graphic lasso (FGL) method (designed for polychoric correlations) 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 across 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 four individually estimated networks. To search for potential clusters of symptoms within the four networks of work addiction, we used a spin-glass algorithm implemented in the igraph 1.2.6 package (Csardi & Nepusz, 2006).

Network Inference

We estimated symptoms centrality based on node strength, a metric equal to the sum of absolute values of all edges of a given node to all other nodes. To compare the four networks in terms of symptoms centrality, we calculated Spearman correlation coefficients between node strength for each pair of networks.

To estimate the average predictability of symptoms, we used the mgm 1.2-11 package (Haslbeck, 2019), which estimates predictability based on individually estimated networks. As this study comprises ordinal data, node predictability indicates how much a node can be predicted by all of its neighbors, beyond what is trivially predicted by the marginal distribution of this node (Haslbeck & Waldorp, 2018).

Network Stability

To investigate the stability of the four 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 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. The correlation stability coefficient higher than .50 is regarded as an indicator of good stability, and the correlation stability coefficient higher than .25 is regarded as an indicator of acceptable stability (Epskamp et al., 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 calculated the global strength estimates (the sum of all absolute edge weights for each network) and tested whether they differed across samples. Moreover, 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.

Results

Descriptive Statistics

Means, standard deviations, skewness, and kurtosis of the seven symptoms of work addiction in the four samples are presented in Table 2. Samples differed in terms of severity of symptomatology (see Table 2).

Network Estimation

The four networks estimated jointly for the four samples are visualized in Figure 1. Due to the large sample size of Sample 1, the four networks were fully connected (i.e., all edges were different from zero). The mean absolute edge weights were equal .13 in each of the four samples. The four networks featured many consistent edges, for example Conflict (6)—Problems (7), but also some edges that considerably differed across networks, for example Withdrawal (5)—Conflict (6). The spin-glass algorithm showed that there were two clusters of symptoms, 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).

Network Inference

Centrality analysis showed that Mood modification (3) had the lowest node strength and that Relapse (4) had the highest node strength in all networks (see Figure 2). Additionally, Salience (1) had systematically low node strength, Tolerance (2), Withdrawal (5), and Problems (7) had systematically high node strength, and Conflict (6) had relatively high variability of node strength across the networks. The node strength was substantially related across the four networks, with correlations ranging between .71 (Network 1 and Network 3) and .96 (Network 2 and Network 4).

Average predictability in the four networks was ranging from 22.6% (Sample 2) to 28.3% (Sample 4) of variance remaining after including marginals, whereas on average, marginals accounted for from 34.1% (Sample 3) to 44.1% (Sample 1; see Figure 1) of the whole variance.

Network Stability

Stability analyses indicated that all four networks were accurately estimated, with small to moderate confidence intervals around the edge weights. The correlation stability coefficients exceeded the recommended threshold of .50 for stability estimation for Network 1 (.75), Network 3 (.52), and

Network 4 (.52), and exceeded the minimal threshold of .25 for stability estimation for Network 2 (.44; Epskamp et al., 2018).

Network Comparison

Spearman correlation coefficients of edge weights for each pair of networks ranged from .93 (Networks 2 and 3) to .98 (Networks 1 and 2), indicating strong similarities between networks (see the comments in the analytical code for details of all results related to network comparison). Global strength did not differ ($p > .05$) across the four networks, and its values were 2.99, 2.91, 2.83, and 2.86 for Network 1, Network 2, Network 3, and Network 4, respectively. In the omnibus tests of the six possible pairwise comparisons, four pairs of networks did not differ significantly from each other. Only Network 1 differed from Network 4 ($p < .001$), and Network 2 differed from Network 3 ($p = .030$), implying that these pairs of networks did not feature exactly the same 21 edge weights. The comparison of Network 1 and Network 4 revealed that of all 21 edges, only four edges (19.0%) differed significantly: Salience (1)—Relapse (4), Mood modification (3)—Withdrawal (5), Withdrawal (5)—Conflict (6), and Relapse (4)—Problems (7). The comparison of Network 2 and Network 3 revealed that of all 21 edges, only three edges (14.3%) differed significantly: Relapse (4)—Withdrawal (5), Salience (1)—Conflict (6), and Relapse (4)—Conflict (6).

Discussion

This study aimed to conceptualize work addiction as a dynamic system of symptoms that are in direct relationships with each other. We estimated the four networks based on four samples that differed in terms of cultural background, age, sociodemographic background, and severity of symptomatology. Below we discuss in detail the results.

Network Estimation

The four networks featured many consistent edges, which comprised two groups of symptoms. The first group included Salience (1), Mood modification (3), and Withdrawal (5) and the second group included Tolerance (2), Relapse (4), Conflict (6), and Problems (7). The two groups of symptoms were connected mainly through the edge between Withdrawal (5)—Relapse (4) and the edge between Salience (1)—Tolerance (2). The results showed that the edge between Conflict (6)—Problems (7) is the strongest in the four networks. It is congruent with addiction conceptualization, assuming that harm caused by the behavior is related to the conflict between the excessive behavior and other spheres of life (Atroszko et al., 2019; Clark et al., 2016; Griffiths et al., 2018; Sussman, 2012). This has significance for potential intervention strategies focused on reducing the role-conflict aspect of work addiction and developing a more balanced lifestyle. Moreover, the results showed that Tolerance (2), the need to increase the "dosage", was directly related to Conflict (6) with other spheres of life. It indicates that potential intervention strategies focused on reducing the amount of time spent working might directly reduce Conflict (6) and thus might indirectly reduce Problems (7). Finally, the results show that edges between Relapse (4)—Withdrawal (5) and between Salience (1)—Tolerance (2) play an important role in connecting the two groups of symptoms and that potential intervention strategies focused on these edges and symptoms might effectively reduce negative consequences of work addiction.

Network Inference

Relapse (4) showed the highest centrality in the network of work addiction. It was measured as a response to a question of whether an individual was told by others to cut down on work without listening to them. In the light of studies showing that more than 90% of addicted individuals do not recognize their problem or seek help (Goldstein et al., 2009), this symptom points to the relevance of the environment in recognizing symptoms of addiction. It has implications for monitoring and studying work addiction, suggesting that observer ratings could be particularly useful in measuring it in family

settings, as well as in the workplace (Atroszko & Atroszko, 2020). However, it suggests that Relapse's (4) high centrality might indicate its outstanding nature as a diagnostic criterion, showing that the problem of individuals addicted to work is best identified when people close to them recognize and communicate their overinvolvement in work, rather than its role in causal chains as it is suggested by the network theory (Borsboom, 2017).

Mood modification (3) showed the lowest centrality and predictability in the network of work addiction. It was measured as a response to a question of whether an individual worked in order to reduce feelings of guilt, anxiety, helplessness, and depression. Addiction is often conceptualized as a result of a pathological mood modification strategy, and it could be argued that Mood modification (3) is crucial as an initial cause for other symptoms to occur. Consequently, low centrality and predictability of Mood modification (3) in the network of work addiction are unexpected. As Mood modification (3) may be present in the early stages of work addiction when other symptoms have not occurred yet, these results may indicate that network analysis based on cross-sectional data may have limited ability to capture the dynamics of symptoms in longer periods (Bos et al., 2017). On the other hand, Mood modification (3) with work activities may be contained within non-pathological limits. For example, an unemployed person may feel significantly better when employed, and it does not indicate that this mood improvement with work is dysfunctional. This interpretation is congruent with a previous study showing that the current wording of Mood modification (3) may poorly differentiate between pathological and non-pathological self-regulation (Bereznowski & Konarski, 2020).

Network Stability and Comparison

The results showed that networks were stable in the four samples and replicated across the four samples. It supported our main hypothesis and showed a high similarity of the networks of work addiction across samples from different countries and of diverse sociodemographic backgrounds. While we observed that the most pronounced differences were between pairs of samples, including working

individuals from different countries and of diverse sociodemographic backgrounds, there was no clear pattern of differences in edge strengths across the two samples.

The high similarity between the networks of symptoms across samples suggests that work addiction is a fairly consistent set of symptoms with high congruence in terms of their interrelationships. These results may indicate that there is a relatively specific psychopathological process responsible for that. These findings constitute a strong argument for considering work addiction a genuine diagnosis that reflects a coherent pattern of behavior consistently related to harm and distress of clinical significance. (Atroszko et al., 2019; Griffiths et al., 2018).

Strengths and Limitations

This is the first empirical investigation of the topology of the network of work addiction. The investigation was performed in four large samples that differed in terms of nationality and sociodemographic background. Work addiction was measured with the same instrument (i.e., the BWAS) in each sample. The four networks were estimated using joint network estimation and compared quantitatively as well as qualitatively. Consequently, this study contributes to the still scant literature on the replicability in the network area of research; however, generalizability of the work addiction networks, based on different measures of work addiction, needs to be further investigated (Borsboom et al., 2017; Forbes et al., 2017a, 2017b).

In terms of limitations, the four samples were predominantly female and 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 networks' parameters and reduce the validity of the results. Last but not least, this study did not account for the effects of other mental disorders and

psychological constructs (e.g., work engagement; Di Stefano & Gaudiino, 2019), which may influence the direct relationships between work addiction symptoms.

Conclusions and Future Studies Directions

This study showed that the network approach constitutes a promising framework for studying work addiction. The dynamic system of the symptoms of work addiction was almost identical for both the Norwegian and Polish samples, and that the minor differences found between the networks were not clearly associated with nationality or sociodemographic background.

On the other hand, this study highlighted two issues associated with the interpretation of the results of network analysis. Firstly, when work addiction is analyzed at a symptom level, the wordings of all items are remarkably important. Network analysis requires the development of measures with precise operational definitions and particular thoroughness during the formulation of the wording of items measuring symptoms (Fried, 2017; see also Bereznowski & Konarski, 2020). Secondly, this study showed that the meaning of symptoms centrality and predictability in cross-sectional networks requires more conceptual clarification. It is uncertain whether they represent symptom's central role in causal chains or symptom's outstanding nature as diagnostic indicators, which have been previously described as the distinction between core and peripheral symptoms of addiction (Charlton & Danforth, 2007; see also Bos et al., 2017; Bringmann et al., 2019; Golino & Epskamp, 2017; Rozgonjuk et al., 2020).

Future studies should investigate networks including work addiction and other work-related phenomena, as well as networks based on longitudinal data. These should include replication of the current study on study addiction conceptualized as an early form of work addiction (Atroszko, 2015; Atroszko et al., 2016) and longitudinal relationships between networks of study and work addiction. 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. The network approach may prove useful in clarifying the relationship between work addiction and anankastia/OCPD, which was suggested to be its major risk factor (Atroszko, 2019b; Atroszko et al., 2020). Finally, intensive longitudinal methods will allow investigating the assumption that cross-sectional data is a good representation of a dynamic process of work addiction within individuals.

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Table 1

Sociodemographic Characteristics of the Four Samples

	Sample 1	Sample 2	Sample 3	Sample 4	Test of differences across samples
Description	General population	Recent graduates	General population	Recent graduates	
Nationality	Norwegian	Norwegian	Polish	Polish	
<i>N</i>	16,426	764	719	711	
Sex					$\chi^2(3) = 118.41, p < .001$
Female	10,487 (63.8%)	541 (70.8%)	509 (70.8%)	578 (81.3%)	
Male	5,939 (36.2%)	223 (29.2%)	200 (27.8%)	133 (18.7%)	
No answer	0 (0.0%)	0 (0.0%)	10 (1.4%)	0 (0.0%)	
Age (<i>M</i> [<i>SD</i>])	37.31 (11.36)	29.76 (7.12)	36.39 (11.36)	25.58 (3.41)	$F(3, 18607) = 357.59, p < .001$
Age (range)	16–75	21–61	20–79	22–51	
Marital status					$\chi^2(3) = 21.44, p < .001$
In a relationship	11,831 (72.0%)	565 (74.0%)	567 (78.9%)	496 (69.8%)	
Not in a relationship	4,595 (28.0%)	199 (26.0%)	148 (20.6%)	215 (30.2%)	
No answer	0 (0.0%)	0 (0.0%)	4 (0.6%)	0 (0.0%)	
Numer of children	NA				$\chi^2(8) = 386.84, p < .001$
0	NA	558 (73.0%)	290 (40.3%)	644 (90.6%)	
1	NA	82 (10.7%)	156 (21.7%)	51 (7.2%)	

2	NA	77 (10.1%)	168 (23.4%)	16 (2.3%)	
3	NA	29 (3.8%)	32 (4.5%)	0 (0.0%)	
4 or more	NA	18 (2.4%)	14 (1.9%)	0 (0.0%)	
No answer	NA	0 (0.0%)	59 (8.2%)	0 (0.0%)	
Highest completed education					$\chi^2(10) = 1379.30, p < .001$
Primary school	782 (4.8%)	0 (0.0%)	NA	0 (0.0%)	
Vocational school	3,010 (18.3%)	0 (0.0%)	NA	0 (0.0%)	
High school	3,413 (20.8%)	29 (3.8%) ^a	NA	0 (0.0%)	
Bachelor's degree	6,045 (36.8%)	444 (58.1%)	NA	285 (40.1%) ^b	
Master's degree	2,933 (17.9%)	289 (37.8%)	NA	420 (59.1%)	
PhD	243 (1.5%)	2 (0.3%)	NA	6 (0.8%)	
Working hours per week (<i>M</i> [<i>SD</i>])	NA	37.45 (7.23)	45.53 (11.73)	39.76 (10.44)	$F(2, 2170) = 128.00, p < .001$
Working hours per week (Range)	NA	8–72	4–98	2–100	
Work status					$\chi^2(3) = 75.81, p < .001$
Full-time worker	12,961 (78.9%)	636 (83.2%)	640 (89.0%)	582 (82.9%)	
Part-time worker	3,465 (21.1%)	128 (16.8%)	61 (8.5%)	120 (17.1%)	
No answer	0 (0.0%)	0 (0.0%)	18 (2.5%)	0 (0.0%)	

Gross income
(categories)^{cd}

Category 1 (C1)	778 (4.7%)	15 (2.0%)	82 (11.4%)	82 (11.5%)	
Category 2 (C2)	941 (5.7%)	58 (7.6%)	116 (16.1%)	285 (40.1%)	
Category 3 (C3)	1,250 (7.6%)	318 (41.6%)	126 (17.5%)	197 (27.7%)	
Category 4 (C4)	3,035 (18.5%)	304 (39.8%)	79 (11.0%)	67 (9.4%)	
Category 5 (C5)	4,336 (26.4%)	39 (5.1%)	61 (8.5%)	24 (3.4%)	
Category 6 (C6)	2,675 (16.3%)	14 (1.8%)	24 (3.3%)	21 (3.0%)	
Category 7 (C7)	1,269 (7.7%)	1 (0.1%)	4 (0.6%)	7 (1.0%)	
Category 8 (C8)	768 (4.7%)	2 (0.3%)	8 (1.1%)	4 (0.6%)	
Category 9 (C9)	459 (2.8%)	0 (0.0%)	7 (1.0%)	0 (0.0%)	
Category 10 (C10)	270 (1.6%)	0 (0.0%)	2 (0.3%)	1 (0.1%)	
Category 11 (C11)	645 (3.9%)	0 (0.0%)	4 (0.6%)	4 (0.6%)	
No Answer	0 (0.0%)	13 (1.7%)	201 (28.0%)	19 (2.7%)	
Gross income (<i>M</i> [<i>SD</i>]) ^c	NA	NA	46 079 PLN (33 054.24)	NA	
Gross income (range) ^c	NA	NA	0–200 000 PLN	NA	
Subjective socioeconomic	NA	4.74 (1.36)	NA	5.28 (1.43)	$t(1448) = -7.29,$

status (M [SD]) $p < 0.001$

Gathered	In the first half of 2014	In October and November of 2016	From January 2014 to July 2016	In October 2016
Symptom severity (M [SD])	2.06 (0.33)	2.12 (0.42)	2.47 (0.36)	2.27 (0.37)
More details in	Andreassen et al., 2016	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 across samples. In Sample 1: C1 = 0–99 999 NOK, C2 = 100 000–199 999 NOK, C3 = 200 000–299 999 NOK, C4 = 300 000–399 999 NOK, C5 = 400 000–499 999 NOK, C6 = 500 000–599 999 NOK, C7 = 600 000–699 999 NOK, C8 = 700 000–799 999 NOK, C9 = 800 000–899 999 NOK, C10 = 900 000–999 999 NOK, C11 = 1 000 999 NOK or more. In Sample 2: 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 3 the open response on gross income was recoded to match categories in Sample 4. In Sample 4: 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

No.	Symptom	Skewness (Kurtosis)				<i>M (SD)</i>				Test of difference s across samples
		Sample 1	Sample 2	Sample 3	Sample 4	Sample 1	Sample 2	Sample 3	Sample 4	
1	Salience	0.66 (2.47)	0.69 (2.59)	0.16 (2.05)	0.44 (2.30)	2.00 (1.02)	2.00 (0.99)	2.53 (1.13)	2.19 (1.01)	$F(3, 18616) = 68.30, p < 0.001$
2	Tolerance	0.03 (2.17)	-0.01 (2.25)	-0.32 (2.31)	-0.09 (2.21)	2.67 (1.08)	2.74 (1.05)	3.18 (1.04)	2.85 (1.04)	$F(3, 18616) = 55.08, p < 0.001$
3	Mood modificati on	1.30 (3.73)	1.49 (4.44)	0.60 (2.19)	0.95 (2.90)	1.70 (1.00)	1.59 (0.91)	2.18 (1.18)	1.93 (1.08)	$F(3, 18616) = 66.57, p < 0.001$
4	Relapse	1.17 (3.45)	1.15 (3.45)	0.42 (2.04)	0.82 (2.53)	1.74 (0.99)	1.78 (1.02)	2.37 (1.21)	2.06 (1.19)	$F(3, 18616) = 106.90, p < 0.001$
5	Withdrawal	0.70 (2.55)	0.47 (2.26)	0.59 (2.43)	0.78 (2.78)	2.05 (1.07)	2.24 (1.11)	2.23 (1.15)	1.99 (1.04)	$F(3, 18616) = 14.24, p < 0.001$
6	Conflict	0.49 (2.16)	0.18 (2.19)	0.08 (1.89)	0.09 (1.97)	2.29 (1.19)	2.55 (1.12)	2.66 (1.23)	2.72 (1.22)	$F(3, 18616) = 59.29, p < 0.001$
7	Problems	0.86 (2.83)	0.92 (3.07)	0.57 (2.18)	0.74 (2.49)	1.97 (1.08)	1.92 (1.03)	2.17 (1.16)	2.13 (1.18)	$F(3, 18616) = 12.83, p < 0.001$

Sample 1

Sample 2

Sample 3

Sample 4

Figure 1. The four regularized partial correlation networks estimated jointly for the four samples. Solid lines represent positive edges and dashed lines represent negative edges. Line thickness and darkness indicate the strength of a relationship. The lighter gray area in the ring around a node represents predictability based on the variance of a symptom explained by all of its neighbors and the darker gray area in the ring around a node represent predictability based on the marginal distribution of a node. Node numbers correspond to symptom numbers in Table 2.

Figure 2. The standardized node strength of the seven work addiction symptoms in the four samples.