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

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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, and 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 \cdot Network analysis \cdot Network approach \cdot Work addiction \cdot Work engagement \cdot Workaholism

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

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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 node 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 node 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 and Konarski (2020) and 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 (Bailey 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).

Work engagement and compulsive overworking are two different subtypes of heavy work investment (Harpaz & Snir, 2014), which are similar on the surface but differ in terms of motivation, antecedents, and consequences (Clark & Michel, 2014; Taris et al., 2014; detailed discussion of similarities and differences between these two phenomena is beyond the scope of this paper; for an elaborated comparison between compulsive overworking and work engagement, we refer the reader to Harpaz and Snir (2014)). 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 (Clark et al., 2016; Di Stefano & Gaudiino, 2019). However, these two studies used somewhat different methodologies, and their results point to some important issues in the measurement of work addiction and work engagement.

The first difference between the two meta-analyses was that Clark et al. (2016) included all studies focused on the relationship between work addiction and work engagement irrespectively of used instruments, while Di Stefano and Gaudiino (2019) included in the meta-analysis only studies which measured work addiction with the Dutch Work Addiction Scale (DUWAS; Schaufeli et al., 2006, 2008) and work engagement with the Utrecht Work Engagement Scale (UWES; Schaufeli et al., 2002, 2006). The second difference between the two meta-analyses was that Clark et al. (2016) combined correlation coefficients of different dimensions of work addiction with work engagement dimensions in a single study into a composite, while Di Stefano and Gaudiino (2019) differentiated between working excessively and working compulsively. Clark et al. (2016) showed that work addiction was weakly positively correlated with general work engagement (estimated r equaled 0.05), absorption (estimated r equaled 0.09), and nonsignificantly correlated with vigor and dedication (estimated rs equaled -0.01 and 0.03, respectively). Di Stefano and Gaudiino (2019) showed that working compulsively was weakly positively correlated with absorption (estimated g equaled 0.28 (after converging effect sizes r equaled 0.15)) and nonsignificantly correlated with vigor and dedication (estimated gs equaled 0.01 and -0.02, respectively (after converting effect sizes rs equaled 0.01 and -0.02, respectively)). Working excessively was weakly positively correlated with absorption and dedication (estimated gs equaled 0.34 and 0.14, respectively (after converting effect sizes rs equaled 0.17 and 0.09)), and nonsignificantly correlated with vigor (estimated g equaled 0.04 (after converting effect sizes r equaled (0.02)). These results show that a nuanced approach to investigating the relationship between work addiction and components of work engagement is indispensable to properly capture the nature of these phenomena.

The positive relationship between work addiction and work engagement is a matter of high-intensity working shared between these two phenomena which presents itself in the content overlap between absorption and some symptoms of work addiction (Di Stefano & Gaudiino, 2019). Based on a model of micro-, meso-, and macro-level risk factors (Atro-szko et al., 2020), we argue that among vulnerable individuals (e.g., highly perfectionistic) under certain external circumstances (for example, when an individual experiences high workplace stress, a work-family conflict, or have unsatisfying personal relationships), this shared component of high-intensity working and being engrossed in work could lead to developing work addiction. This process could be observed at the symptom level of work addiction. Consequently, in this study, we used a network approach to investigate relationships between symptoms of work addiction and components of work engagement.

Based on the following part of the absorption definition "one has difficulties with detaching oneself from work" (Schaufeli et al., 2002, p. 75), 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).

However, it should be noted that even though results of cross-sectional partial correlation networks could reflect within-subject relationships (see Rodebaugh et al. (2018) and von Klipstein et al. (2021)), longitudinal studies are highly warranted to confirm their results.

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 10 years older) who most notably were not all university graduates.

Table 1 presents detailed sociodemographic characteristics of the three samples after the listwise deletion of observations with missing data on work addiction or work engagement and their statistical comparison. The three samples differed significantly in terms of all sociodemographic characteristics. Sample 3 included a higher proportion of women (81.6%) than sample 1 (71.0%) and sample 2 (70.6%). The mean age of participants was the highest in sample 2 (M=36.24) and the lowest in sample 3 (M=25.58). The highest proportion of individuals in a relationship was in sample 2 (78.7%) and the lowest ratio was in sample 3 (70.2%). Sample 2 included the highest proportion of individuals with children (58.9%), and sample 3 included the lowest proportion of individuals with children (9.5%). Most individuals in sample 1 had a bachelor's degree (57.9%), and most individuals in sample 3 had a master's degree (59.1%); individuals in sample 2 were not asked about their education. Mean working hours per week were the highest in sample 2 (M=45.61) and the lowest in sample 1 (M = 37.48). Sample 2 included a higher proportion of individuals working full-time (89.2%) than sample 1 (83.3%) and sample 3 (83.2%). Individuals in sample 3 had a higher level of subjective socioeconomic status (M=5.28) than individuals in sample 1 (M = 4.74); individuals in sample 2 were not asked about their subjective socioeconomic status. Detailed information regarding compensation, missing data, and removal of observations with missing data are presented in the Supplemental Materials.

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 (e.g., "How often during the last year have you worked in order to reduce feelings of guilt, anxiety, helplessness and depression?" measures mood modification and "How often during the last year have you worked so much that it has negatively influenced your health?" measures tolerance). 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), and 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 0.85 for sample 1, 0.84 for sample 2, and 0.84 for sample 3.

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	Sample 1	Sample 2	Sample 3	Test of differences between samples
Description	Recent graduates	General population	Recent graduates	
Nationality	Norwegian	Polish	Polish	
Ν	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 (M [SD])	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				$\chi^2(2) = 15.05, p < .001$
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%)	

Table 1 (continued)				
	Sample 1	Sample 2	Sample 3	Test of differences between samples
Working hours per week (M [SD])	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 $(M [SD])^c$	NA	46 029.08 (33 104.21) PLN	NA	
Gross income (range) ^c	NA	0-200 000 PLN	NA	
Subjective socioeconomic status (M [SD])	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	From January 2014 to July 2016	In October 2016	
Symptom severity $(M [SD])$	2.12 (0.75)	2.48 (0.83)	2.27 (0.80)	
Work engagement $(M [SD])$	15.30 (3.51)	14.50 (3.86)	14.10 (3.65)	

	Sample 1	Sample 2	Sample 3	test of differences between samples
More details in	Atroszko et al. (2016)	Atroszko et al. (2017)	Atroszko et al. (2016)	
^a These individuals declared that trable with categories in other stuce b ^b Seventeen individuals declared t master's degree (this level of edu education is bachelor's degree	^a These individuals declared that their highest completed level of education is a 1-year program 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 ^b Seventeen individuals declared that their highest completed level of postgraduate studies whose highest completed level of education is high school ^b Seventeen 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.	i is a 1-year program at a university as individuals whose highest compl ation is some kind of postgraduate n other studies); therefore, we class	(i.e., Årsenhet in Norweg eted level of education is l studies which can be com fifed all of them as indivi	ian; this level of education is incompa- nigh school pleted both after bachelor's degree and duals whose highest completed level of
^v Past year personal annual income before tax in Norwegiai C1=0-150 000 NOK, C2=150 001-300 000 NOK, C3= $(7 = 900 001-1 050 000 NOK, C8=1 050 001-1 200 000 2, the open response on gross income was recoded to mate C4=51 001-68 000 PLN, C5=68 001-85 000 PLN, C5=C10=153 001-170 000 PLN, C11=170 000 PLN or more$	² Past year personal annual income before tax in Norwegian and Polish currencies (i.e., NOK and PLN). ⁴ Categories 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=1 200 001-1 350 000-150 000 NOK, C11=1 500 001 or more. In sample 2, the open response on gross income was recoded to match categories in sample 3: 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=153 000 PLN, C1=150 000 PLN, C11=170 000 PLN, C1=170 000 PLN, C1=170 000 PLN, C11=170 000 PLN, C1=150 000 PLN, C7=102 001-119 000 PLN, C8=119 001-136 000 PLN, C9=136 001-153 000 PLN, C10=153 000 PLN, C10=153 000 PLN, C10=150 000 PLN, C10=150 000 PLN, C9=136 001-153 000 PLN, C10=153 000 PLN, C10=150 000 PLN, C10=150 000 PLN, C9=136 001-153 000 PLN, C10=153 000 PLN, C10=150 000 PLN, C10=150 000 PLN, C10=150 000 PLN, C9=136 001-153 000 PLN, C10=150 000 PLN, C9=136 001-153 000 PLN, C10=153 001-170 000 PLN, C11=170 000 PLN or more	urrencies (i.e., NOK and PLN). ^d C: 00 NOK, C4=450 001–600 000 N 200 001–1 350 000 NOK, C10=1 1 sample 3. In sample 3: C1=0–17 000 PLN, C7=102 001–119 000 F	tegories for gross income OK, C5 = 600 001–750 00 350 001–1 500 000 NOI 000 PLN, C2 = 17 001–3 1LN, C8 = 119 001–136 (varied between samples. In sample 1: 00 NOK, C6=750 001-900 000 NOK, C C11 = 1 500 001 or more. In sample 4 000 PLN, C3 = 34 001-51 000 PLN, 000 PLN, C9 = 136 001-153 000 PLN,

Table 1 (continued)

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 (e.g., "At my work, I feel bursting with energy."), dedication (e.g., "I am enthusiastic about my job."), and absorption (e.g., "I am immersed in my work."). 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 0.89 (vigor), 0.89 (dedication), and 0.84 (absorption) for sample 1: 0.85 (vigor), 0.82 (dedication), and 0.78 (absorption) for sample 2, and 0.84 (vigor), 0.80 (dedication), and 0.76 (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 crossvalidation 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 0.70 or higher. A correlation stability coefficient higher than 0.50 is regarded as an indicator of good stability, and a correlation 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 neighbors (R^2). For ordinal data (symptoms of work addiction), 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 (for a detailed explanation, see Haslbeck and 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).

Network Estimation

The three networks estimated jointly for the three samples are visualized in Fig. 1. The network density equaled 0.93 (42/45 edges) for network 1, 0.89 (40/45 edges) for network 2, and 0.87 (39/45 edges) for network 3. The mean absolute edge weights equaled 0.11, 0.10, and 0.10 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 Fig. 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).

		Skewness (kurtosis)	sis)		M (SD)			Test of differences between samples
No	Node	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
б	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
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
9	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
×	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
6	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

 Table 2
 Overview of the Seven Symptoms of Work Addiction and the Three Dimensions of Work Engagement

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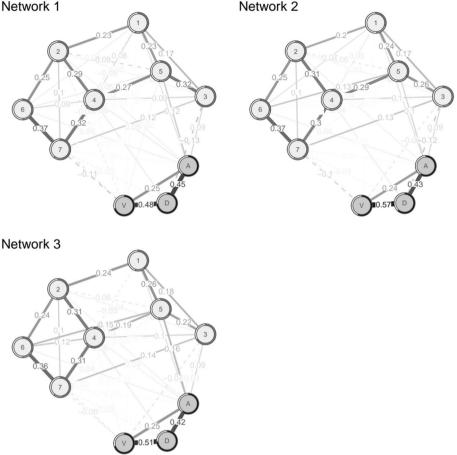


Fig. 1 The three regularized partial correlation networks estimated jointly for the three samples. The lighter gray nodes represent the symptoms of work addiction, and the darker gray nodes represent the dimensions of work engagement. Solid lines represent positive edges, and dashed lines represent negative edges. Line thickness and darkness indicate the strength of a relationship. In the case of symptoms of work addiction, the lighter 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. 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

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 0.25 for stable estimation of centrality indices (Epskamp et al., 2018) for network 2 (0.44) and did not exceed this threshold for network 1 (0.21) and network 3 (0.13). 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 equaled 1.20), and salience (1) was the least central node (unstandardized value equaled 0.80). However, the standard version of the node strength poorly differentiated node centrality in the three networks (see panel A on Fig. 2). Spearman correlation coefficients of the standard version of the node strength equaled 0.82 for network 1 and network 2, 0.88 for network 1 and network 3, and 0.62 for network 2 and network 3.

The bridge strength showed that mood modification (3) was the most central symptom of work addiction (unstandardized value equaled 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 equaled 0.42 for network 1, 0.35 for network 2, and 0.45 for network 3; see panel B on Fig. 2). Spearman correlation coefficients of the bridge strength equaled 0.95 for network 1 and network 2, 0.89 for network 1 and network 3, and 0.87 for network 2 and network 3.

Predictability analysis showed that conflict (6) was the most predictable symptom of work addiction (average predictability equaled 22.7%) and that mood modification (3) was the least predictable symptom of work addiction (average predictability equaled 8.4%; see Fig. 1). The three dimensions of work engagement showed a similarly high level of predictability, and dedication (D) was the most predictable one (average predictability equaled 66.2%). Average predictability equaled 36.9% in network 1, 37.1% in network 2, and 38.6% in network 3.

Network Comparison

Spearman correlation coefficients of edge weights equaled 0.95 for network 1 and network 2, 0.95 for network 1 and network 3, and 0.94 for network 2 and network 3. In the omnibus tests of the three possible pairwise comparisons, network 1 differed significantly from network 2 (p=0.032), network 1 differed significantly from network 3 (p=0.042),

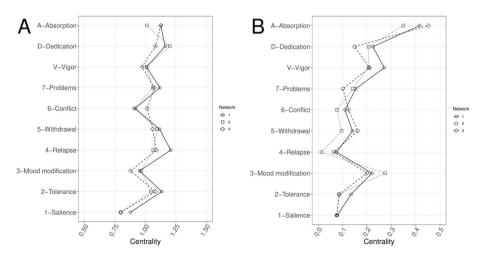


Fig.2 A The unstandardized values of the standard version of the node strength in the three networks. B The unstandardized values of the bridge strength in the three networks

and network 2 did not differ significantly from network 3 (p=0.124). 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), and 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 > 0.05) 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)—dedication (D) with edge weights of 0.10, 0.10, and -0.10, respectively. The most variable edges connecting the seven symptoms of work engagement were problems (7)—vigor (V), mood modification (3)—dedication (D), and withdrawal (5)—absorption (A), with standard edviations of 0.06, 0.05, and 0.05, respectively.

The correlation stability coefficient of the cross-sample network was equal to 0.52 and exceeded the recommended threshold of 0.50 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 equaled 1.03), salience (1) was the least central symptom of work addiction (unstandardized value equaled 0.75), and dedication (D) was the most central dimension of work engagement (unstandardized value equaled 1.11). The bridge strength showed that mood modification (3) was the most central symptom of work addiction (unstandardized value equaled 0.26), relapse (4) was the least central symptom of work addiction (unstandardized value equaled 0.00), and absorption (A) was the most central dimension of work engagement (unstandardized value equaled 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 Norwe-gian 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.

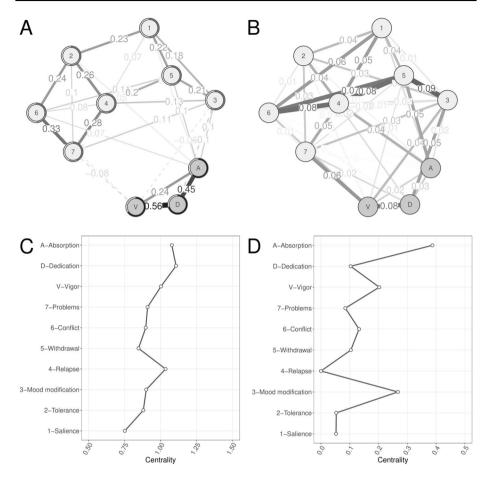


Fig. 3 A The cross-sample network, which was obtained by pooling all observations into one sample, and **B** the cross-sample variability network in which edge weights represent the standard deviation of edge weights between the three jointly estimated networks. The lighter gray nodes represent the symptoms of work addiction, and the darker gray 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 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. 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). **C** The unstandardized values of the standard version of the node strength in the cross-sample network. **D** The unstandardized values of the bridge strength in the cross-sample network

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 Figs. 1 and 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 0.10), 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 and 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 Fig. 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 nonpathological 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 and 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 and 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, b) 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 Study 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 modeling. Last but not least, future studies should investigate the properties of the bridge strength index introduced in this study.

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Author Contribution PB assisted with obtaining funding, literature search, study design and concept, statistical analyses, data interpretation, generation of the initial draft of the manuscript, manuscript preparation and editing, and final editing; AB assisted with literature search, data interpretation, generation of the initial draft of the manuscript, manuscript preparation and editing, and final editing; PAA assisted with literature search, study design and concept, data collection, data interpretation, manuscript preparation and editing, and final editing; RK assisted with study design and concept, manuscript preparation and editing, and final editing.

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Declarations

Ethics The study was carried out in accordance with the Declaration of Helsinki. All gathered data was anonymous, and participants were informed about all the proper details about the study and their role in it, including that they can withdraw at any point. Attaining formal and written informed consent was not regarded as necessary as voluntary completion of the questionnaires was regarded as providing consent, and no medical information was gathered.

Conflict of Interest The authors declare no competing interests.

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