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Unravelling the web of addictions: A network analysis approach

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ABSTRACT

Background: Common elements across different forms of addiction suggest the possibility of comorbid addictions, as well as the transition/replacement of one form of addiction with another. This study aimed to conduct a Network analysis of symptoms of 10 forms of addictive behaviors to examine their behavioral commonalities/interrelations. **Methods:** To address this aim, an online community sample of 968 adult participants (33.6% women, 66.4% men) completed self-rating questionnaires covering a range of addictive behaviors including alcohol, drugs, tobacco, sex, online gambling, internet use, internet gaming, social media use, shopping, and exercise. Their responses were examined with regularized partial correlation network analysis (EBICglasso) and a community detection algorithm (Walktrap) to identify: (a) specific links between neighboring forms of addiction; and (b) clustering of symptoms of addiction. **Results:** Findings showed positive network connections across different addictive behaviors, with addictive tendencies towards gambling showing the highest centrality, sequentially followed by addictive tendencies towards internet use, internet gaming, alcohol, shopping, social media use, drugs, sex, smoking, and exercise. **Conclusion:** Symptoms associated with disordered drug use and gambling are suggested to maintain severity of addictive disorders and increase the likelihood of developing cross addictive behaviors. Clinical implications for the assessment and treatment of addiction comorbidities and the replacement of one form of addiction with another are discussed considering these findings.

1. Introduction

The last 20 years saw a paradigm shift in the conceptualization of addiction, suggesting that addictive behaviors can take place in alternative realms which may not necessarily involve the use of substances (i. e., behavioral addictions; APA, 2013; Burleigh et al., 2019; Demetrovics & Griffiths, 2012; Griffiths, 1996; Griffiths, 2005; Griffiths, 2017; Kardefelt-Winther et al., 2017; Sixto-Costoya et al., 2021; West & Brown, 2013; Wong et al., 2012). These include a range of diverse behaviors such as excessive online gambling (Griffiths, 1995; Montiel et al., 2021), hypersexual activity (Carnes, 1983; Krueger, 2016), problematic internet use (Anderson et al., 2017; Stavropoulos et al., 2013; Van Rooij et al., 2017), disordered gaming (Pontes et al., 2021; Stavropoulos et al., 2019), problematic social media use (Pontes et al., 2018; Schivinski et al., 2020), compulsive shopping (Andreassen et al., 2015; Müller et al., 2021), and problematic exercising (Beck Lichtenstein & Jensen, 2016; Beck Lichtenstein et al., 2017).

Nonetheless, the acknowledgment and interpretation of such problematic behaviors as formal diagnostic categories of addictions has been a source of inconsistencies in the literature (Petry et al., 2018). For instance, while the World Health Organization (WHO, 2021) acknowledges problematic gaming and gambling as official diagnostic classifications/ disorders, under the broader category of addictions, it does not enlist other similar problematic behaviors like the abuse of social media. In that context, recently proposed taxonomies introduce the notion of *Internet Use Disorders* to include addictive behaviors related to problematic internet use in general (Montag et al., 2021). However, concerns are highlighted regarding the risk of over-pathologizing such everyday life behaviors, which in some cases may even constitute one's efficient coping strategies (Kardefelt-Winther et al., 2017). To enhance the clarity in the field further, research has been invited (see for instance *Internet Gaming Disorder* [IGD], American Psychiatric Association [APA], 2013).

Addressing such invitations, a growing body of research suggests that these addictive/problematic behaviors tend to co-occur rather than

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present in isolation (Farré et al., 2015; Haylet et al., 2004; Lee et al., 2018; Lorains et al., 2011; Martin et al., 2013a; Mérelle et al., 2017; Müller & Montag, 2017; Szabo et al., 2017). Indeed, research supports that predisposing factors such as depression (Xu et al., 2020), anxiety (Stavropoulos et al., 2017), maladaptive strategies (Ostovar et al., 2021), and adverse life experiences (Farré et al., 2015), may act as antecedents leading to the development and maintenance of co-occurring addictive behaviors (see also the I-PACE model explaining the rise of addictive behaviors, in particular in the online realm; Brand et al., 2016, 2019). Similarly, evidence indicates that commonalities across forms of addictions might act as a ‘gateway’ increasing the likelihood of comorbid addictions (Burleigh et al., 2019; Rozgonjuk et al., 2021). For example, Delfabbro and King (2020) suggest that the ‘digital convergence’ of certain online activities facilitates the comorbid presentations of addictions in online environments (i.e., gambling, gaming, disordered internet use, etc.).

Additionally, empirical evidence suggests that common elements across different symptoms of addiction may increase the likelihood of developing cross-addictive behaviours in two important ways (Ford & Håkansson, 2020; Fuss et al., 2019; Tang et al., 2020). Firstly, common elements may facilitate a cycle of reciprocity, exacerbating the risk of transitioning from one addictive behavior to another (e.g., one abuses alcohol and while drinking progressively develops disordered gaming behaviors; Burleigh et al., 2019). Secondly, individuals may seek gratification through alternative addictive behaviors while aiming to disengage from a previously established addiction (e.g., drug abusers may substitute their use of substances with alcohol while aiming to abstain from the first; Brown et al., 2021; Haylett et al., 2004). Thus, there is a need to fully understand the degree of potential interrelation between different forms of addictions to be able to better address their comorbidities, as well as reducing the risk of addiction substitution.

To date, evidence for the interrelations between different forms of addiction has been examined via correlational analysis (Estévez et al., 2017; Montag et al., 2015; Müller et al., 2015; Müller et al., 2017), logistic regression (Mérelle et al., 2017), chi square (Martin et al., 2013b), and structural equation modelling (Lee et al., 2018), among other methods. While these methodologies enable researchers to understand the degree of relationship between constructs, several limitations can be outlined.

Firstly, these methods place emphasis on commonalities across different forms of addictive behaviors at the construct level. In other words, these methods view addictive behaviors as syndromes inclusive of various symptoms (e.g. disordered gaming with disordered alcohol use), rather than examining how distinct symptoms of different addictions may link with each other (e.g., how preoccupation with gaming might relate with alcohol withdrawal; van Rooij et al., 2017). Secondly, these methods provide limited insight into the relative importance of certain symptoms of addiction compared to others (e.g., whether mood-modification is more central/ important compared to relapse and interpersonal conflicts for the diagnosis of pathological gambling). Lastly, these methodologies do not examine the potential ‘clustering’ of distinct symptoms of different addictive behaviors (e.g., whether symptoms of online gambling sufficiently related to provide evidence of a form of behavioural addiction that is distinct from other forms of online disordered activity). These limitations can all be circumvented using a network analysis approach.

1.1. Network analysis (NA)

NA involves estimating relationships between variables/behaviors, without assuming the existence of a specific latent construct (e.g., an addiction syndrome), that can be visualized by a graphical model (Epskamp et al., 2018). A psychopathology network involves a set of variables/behaviors (i.e., nodes) that are connected through non-causal relationships (i.e., undirected edges; Borsboom & Cramer, 2013). This novel approach has been successfully employed in psychiatry/

psychology research to advance our conceptualization / definition of different presentations of psychopathology due to a series of attractive features (Borsboom & Cramer, 2013; Fried et al., 2017; van Borkulo et al., 2015).

Firstly, rather than emphasising interrelations at the construct level (e.g., gaming disorder), NA evaluates relationships between psychopathology symptoms (e.g., gaming preoccupation, gaming tolerance and gaming withdrawal; Fried et al., 2017). At this point, it should be noted that the current dominant perspective in psychology/psychiatry suggests that mental disorders are a reflection of a group of symptoms (i.e., reflective approach), and thus could be explained by a latent (or unobserved) construct (Borsboom & Cramer, 2013). This implies that a construct is sufficient to explain the disorder and diminishes the importance of specific symptomatology (van Rooij et al., 2017). Alternatively, NA conceptualizes symptoms as mutually interacting and being the cause of the disorder (i.e., formative approach; van Borkulo et al., 2015). Thus, rather than only evaluating comorbidity between constructs, NA allows the examination of comorbidity of symptoms within and across disorders (Fried et al., 2017; Kendler et al., 2020). Such information may be particularly useful considering that comorbid symptoms across different disorders, alternatively known as bridge symptoms, can accommodate either the transition from one disorder to the other, or their co-occurrence (Epskamp et al., 2018).

Secondly, NA provides centrality indices (Hevey, 2018). Complex and heterogeneous networks can include symptoms/behaviours that are more important or central than others due to their relative position within the network structure (Rodrigues, 2019). Thus, while NA estimates the strength of the relationship between symptoms, it also provides centrality indices to understand the importance of each symptom, or cluster of symptoms, exerts on the network (Hevey, 2018). For example, in public health responses to controlling an epidemic, identifying individuals/events with high level of connections, or potential ‘super spreaders’, provides an efficient means for targeted interventions (Pastor-Satorras & Vespignani, 2001). Similarly, in psychopathology networks, understanding the influence of a particular form of addiction (e.g., pathological gambling), and how that might vary across its composing symptoms/ behaviors (e.g., tolerance, preoccupation, withdrawal etc.) could provide crucial knowledge to addressing addictive comorbidities and substitution behaviors (Borsboom & Cramer, 2013; Burleigh et al., 2019).

Finally, NA enables researchers to estimate ‘communities’, or clusters of nodes, according to their position within the network (Hevey, 2018). That is, nodes showing the shortest paths between one another will be clustered together forming communities (Fried et al., 2017). Using graphical features embedded in NA, researchers can visualize the taxonomy of structures, while enabling the identification of neighboring communities (Kendler et al., 2020). In psychopathology networks, communities of symptoms clustered together may either depict different psychopathological entities/ diagnoses and/or represent different comorbidity associations, providing insight into identification of behavioral commonalities (Borsboom & Cramer, 2013).

1.2. Current study

Previous research has provided evidence of comorbid addictive disorders (Delfabbro & King, 2020; Farré et al., 2015; Lee et al., 2018; Lorains et al., 2011; Martin et al., 2013a; Mérelle et al., 2017), and has also suggested the possibility/ risk of substituting one form of addictive behavior with another, while trying to abstain from the first (Haylett et al., 2004; Kim et al., 2021). To the best of the authors’ knowledge, only one study to date has explored the interrelations between a diverse range of different forms of addictions referring to online activities and their composing symptoms via network analysis (Rozgonjuk et al., 2020). However, the current study aims to address symptoms of addictive behaviors related to online and offline activities.

The current study aimed to examine the network structure and

centrality of an extensive series of symptoms of addictive/problematic behaviors referring to the abuse of alcohol, drugs, tobacco, sex, online gambling, internet use, internet gaming, social media use, shopping, and exercise. It was further aimed to detect ‘clusters’ of neighboring forms of the aforementioned problem behaviors. Identifying the network structure of manifestations (e. g preoccupation and/or withdrawal symptoms) of neighboring addictive/problematic behaviors (e.g., alcohol abuse and/or gambling) may assist clinicians in a twofold manner. Firstly, it could enhance clarity regarding the optimum taxonomy of a range of problematic behaviors in relation to formally classified forms of addictions, paving concurrently the way for more robust and effective differential diagnosis procedures (Griffiths, 2005; Haylett et al., 2004). Secondly, it may provide guidelines for more effective prevention and intervention practices, by helping professionals to timely identify and address central symptoms that may relate to higher risk for concurrent and/or prospective development of other addictive behaviors (e.g., higher tolerance to problematic gambling may relate to higher risk for the development of problematic social media use comorbidity more than gambling preoccupation).

2. Method

2.1. Participants

The initial sample comprised 1097 responses, with 129 responses deleted due to being considered invalid (i.e., preview-only responses, spam responses, potential bots, etc.). A normative sample of 968 adults from USA, UK, Australia, and New Zealand was studied. Only English-speaking adults (+18 y.o.) were eligible to participate. Participants’ age ranged from 18 to 64 years ($M_{age} = 29.54, SD = 9.35$) and included 315 females (32.5%; $M_{age} = 30.02, SD = 10.39$), 622 males (64.3%; $M_{age} = 29.46, SD = 8.93$), and 31 non-binary (3.2%; $M_{age} = 26.26, SD = 5.13$). No significant difference in age across gender categories was observed, $F(5, 962) = 1.489, p = .191$. Most participants reported being White/Caucasian (61.5%), and about half of the participants state not to be in a romantic relationship (50.4%). Supplementary Table 1 includes detailed participant sociodemographic information. About a quarter of the participants completed at least high school (27.2%), and about a third of the participants reported to be employed full-time (34.2%). Missing values in participants’ responses were assessed via Mice package in R Studio, and Little’s test determined that missing responses were Missing Completely at Random (MCAR; $\chi^2 = 314.979, df = 281, p = .080$; Van Buuren & Groothuis-Oudshoorn, 2011). Table 1 presents addictive behavior information for the sample, and Table 2 presents a correlation matrix including addictive behaviors and age of participants.

2.2. Measures

Ten different instruments were employed to assess symptom severity

Table 1
Addictive behaviors descriptive statistics (N = 968).

Disorder	N	Min	Max	Males (N = 612)		Females (N = 314)		Non-binary (N = 42)	
				Mean	SD	Mean	SD	Mean	SD
Internet Gaming	957	9	45	18.57	7.26	17.29	6.72	18.54	7.53
Alcohol	963	0	35	4.59	5.98	4.15	5.79	5.43	8.33
Smoking	968	5	25	9.29	3.83	9.15	4.20	8.61	4.43
Drugs	967	0	10	1.63	1.60	1.77	1.75	2.13	2.03
Sex	962	0	24	7.62	5.07	4.86	4.61	5.65	5.00
Social Media	962	6	30	10.98	5.27	13.06	5.69	12.84	6.84
Shopping	958	7	35	12.86	5.66	14.92	5.80	13.42	6.63
Exercise	957	6	36	14.96	6.56	13.61	6.20	10.45	6.34
Gambling	952	11	55	14.02	6.28	12.92	5.07	11.70	2.28
Internet	958	9	45	19.52	7.82	20.63	7.85	22.27	10.81

Note. N = sample size; SD = Standard deviation; Min = Minimum possible value; Max = Maximum possible value; Non-binary participants are those who did not identify as males or females.

including use disorders targeting substance and non-substance areas expressed in online and offline environments (i.e., online gaming, online gambling, internet use, sexual behavior, social media use, shopping, exercise, alcohol use, drug use, and tobacco use). The measurements used in the current study included: the *Internet Gaming Disorder Scale – Short Form* (IGDS9-SF; Pontes & Griffiths, 2016); the *Online Gambling Diagnostic Questionnaire* (OGD-Q; González-Cabrera et al., 2020); the *Internet Disorder Scale - Short Form* (IDS9-SF; Pontes & Griffiths, 2016); the *Bergen-Yale Sex Addiction Scale* (BYSAS; Andreassen et al., 2018); the *Bergen Social Media Addiction Scale* (BSMAS; Andreassen et al., 2016); the *Bergen Shopping Addiction Scale* (BSAS; Andreassen et al., 2015); the *Exercise Addiction Inventory* (EAI; Terry et al., 2004); the *Alcohol Use Disorders Identification Test* (AUDIT; Fleming et al., 1991); the *Drug Abuse Screening Test* (DAST-10; Cocco & Carey, 1998; Skinner, 1982); and the *Cigarette Dependence Scale* (CDS-5; Etter et al., 2003). All instruments showed acceptable internal consistency with Cronbach α ranging from 0.68 to 0.95 and McDonald’s ω 0.88 to 0.95. Supplementary Table 2 presents a description of each instrument and their internal reliability indices.

2.3. Procedure

Upon obtaining ethics approval (application number HRE20-169) from the Victoria University Human Ethics Research Committee (Melbourne, Australia), the study was advertised via email (Victoria University student platform), and social media (Facebook, Instagram, Twitter, and Reddit) to adults in the general community. Eligible participants (i.e., adults) were invited to complete an online survey via Qualtrics link including demographic questions and a battery of questionnaires related to the measures employed in the current study. A Plain Language Information Statement was made available upon accessing the link to ensure participant met eligibility criteria (i.e., adults), provided informed consent, and completed the survey voluntarily. Data was collected between November 2020 and January 2021.

2.4. Statistical analysis - NA

Following suggestions outlined in Epskamp et al. (2018), three steps were completed to estimate and evaluate a network of symptoms of problematic behavior: 1) estimation of statistical model; 2) analysis of network structure; and 3) assessment of accuracy and stability of network parameters (Epskamp et al., 2018; Rodrigues, 2019). Additionally, following suggestions outlined by Christensen et al. (2020), we included a fourth step to identify communities of nodes within the network structure. Steps one to three were conducted using Jeffreys’ Amazing Statistics Program (JASP; JASP team, 2020), and step four was conducted using the EGAnet package in R Studio (Golino, 2021).

Step 1: Evaluation and visualization of networks involves the use of a Gaussian graphical model (GGM) in which edges can be interpreted as

Table 2
Addictive behaviors correlation matrix (including age).

	1	2	3	4	5	6	7	8	9	10
1. Internet Gaming	–									
2. Alcohol	0.066*	–								
3. Smoking	0.051	0.200**	–							
4. Drugs	0.105**	0.377**	0.282**	–						
5. Sex	0.387**	0.164**	0.068*	0.120**	–					
6. Social Media	0.358**	0.143**	0.001	0.103**	0.306**	–				
7. Shopping	0.325**	0.097**	0.080**	0.116**	0.256**	0.429**	–			
8. Exercise	0.072*	0.005	-0.036	-0.035	0.117**	0.145**	0.121**	–		
9. Gambling	0.379**	0.201**	0.089**	0.174**	0.281**	0.266**	0.347**	0.195**	–	
10. Internet	0.688**	0.108**	0.039	0.176**	0.362**	0.516**	0.387**	0.057	0.318**	–
11. Age	-0.244**	0.109**	0.162**	-0.052	-0.112**	-0.163**	-0.141**	-0.044	-0.093**	-0.228**

Note: * $p < .05$; ** $p < .01$

partial correlation coefficients (Epskamp et al., 2018). Considering that the GGM can estimate polychoric correlations, it has been assessed as appropriate to deal with non-equidistant ordinal data (i.e., obtained through Likert-type scales; Fried et al., 2017). Due to the often-unintelligible presentation of complex psychopathology networks, GGM with regularization techniques was employed to minimize spurious edges (Hevey, 2018). For example, the ‘least absolute shrinkage and selection operator’ (LASSO) algorithm employs a tuning parameter (γ) that minimizes the Extended Bayesian Information Criterion (EBIC) to estimate a ‘weighted’ matrix (Epskamp et al., 2018). We employed the EBIC-LASSO to estimate our network, and thus shrink spurious correlations to zero, and increasing the interpretability of the network.

Step 2: The analysis of a network structure can be determined by evaluating the weighted matrix and *Centrality* indices (Epskamp et al., 2018). The weighted matrix quantifies relationships between nodes while accounting for the strength of their relationship, with higher weights representing stronger relationships (Hevey, 2018). Additionally, centrality indices (*Strength*, *Betweenness*, *Closeness*, and *Expected influence*) provide insight into the relative importance of a specific node in comparison with other nodes included in the network (Rodrigues, 2019). *Degree* (also called strength) represents a count of how many non-zero edges a particular node has, with higher counts implying higher importance within the network (Epskamp et al., 2018). *Betweenness* represents the average distance of each node to all others, and *Closeness* represents the inverse sum of all the shortest paths. In NA central (or influential) nodes will have higher frequency of short paths passing through (Hevey, 2018). *Expected influence* represents the sum of edge weights in weighted networks accounting for both positive and negative relationships between nodes (Robinaugh et al., 2016). This index aims to understand the cumulative influence a node has on a network, and thus assess the role it may play in the activation, persistence, and remission of the network (Robinaugh et al., 2016). Finally, identification of ‘bridge’ symptoms (i.e., symptoms connecting with other forms of addiction) can be derived by evaluating the weighted matrix (Vanzhula et al., 2021).

Step 3: Two techniques can be used to evaluate the network accuracy: edge-weight accuracy, and centrality stability. Firstly, edge-weight accuracy can be assessed by estimating 95% confidence intervals (CI) using non-parametric bootstrapped samples (Epskamp et al., 2018). Narrower CIs suggest a more precise estimation of edges. Secondly, centrality stability can be assessed by *case-dropping subset bootstrapping* (Epskamp et al., 2018). This involves dropping incremental percentages of observations (e.g., 25%, 35%, etc.) to determine whether centrality indices remain constant with each subset of observations (Epskamp et al., 2018). Correlation stability coefficients (CS) provide a measure to determine if centrality indices vary significantly between each incremental case-dropping subset, with $CS > 0.5$ indicating appropriate stability (Epskamp et al., 2018; Forbes et al., 2021).

Additionally, a fourth step can be implemented to provide insight into the network taxonomy, and thus identify potential communities of nodes (Golino et al., 2020). While visualization of networks can be

obtained through the graphical EBIC-lasso (EBIC-glasso; Epskamp et al., 2018), exploratory graph analysis (EGA) can enhance visual identification of communities within the network through a dimension reduction process (Christensen et al., 2020; Yang et al., 2016). In this context, EGA uses the Walktrap community detection algorithm within an EBIC-glasso framework to identify the optimum number of dimensions that may be present in the network (Christensen et al., 2020; Golino et al., 2020). The EGA approach has been described as superior to traditional dimension reduction techniques (such as exploratory factor analysis; EFA) because it does not require the researcher to make decisions about rotation of axis (Golino et al., 2020).

3. Results

3.1. Psychopathology network of addiction

To investigate interrelations between symptoms of addictive behaviors, we used the EBIC-glasso with a tuning parameter (γ) of 0.5 and 1000 non-parametric bootstrapped samples to estimate a network of symptoms of addictive behaviors. This included 79 symptoms of 10 forms of addictive behaviors including alcohol, drugs, tobacco, sex, online gambling, internet use, internet gaming, social media use, shopping, and exercise (Fig. 1). Of 3081 possible edge weights, 1112 were non-zero (36.1%), with 673 positive relationships (60.5%). Supplementary table 4 presents the weighted edge matrix.

The strongest estimated positive edges were observed between BYSAS-2 (*Felt an urge to masturbate*) and BYSAS-3 (*Used sex/masturbation to escape from personal problems*; 0.62); between IGD-9 (*lost a relationship because of online gaming*) and IDS-9 (*lost a relationship due to Internet usage*; 0.48); and between BSMAS-1 (*spent a lot of time thinking about social media*) and BSMAS-2 (*felt an urge to use social media more and more*; 0.46).

3.2. Centrality indices

The standardized estimates of the centrality indices for degree, betweenness, closeness, and expected influence are presented in Fig. 2. Considering degree, the nodes with most connections were OGDQ-10 (*asked someone for money due to gambling*), AUDIT-6 (*needed a first drink in the morning*), and DAST-2 (*abuse more than one drug at a time*). Considering betweenness, the nodes with the shortest distance relative to other nodes were AUDIT-6 (*needed a first drink in the morning*), OGDQ-10 (*asked someone for money due to gambling*), DAST-5 (*feel guilty about drug use*). Considering closeness, nodes with the highest inverse sum of shortest paths were AUDIT-6 (*needed a first drink in the morning*), OGDQ-10 (*asked someone for money due to gambling*), DAST-7 (*neglected your family because of drug use*). Also see Supplementary Table 3 for detailed information about centrality indices discriminated by symptom.

Considering expected influence, nodes with highest sum of edge weights accounting for both positive and negative relationships were

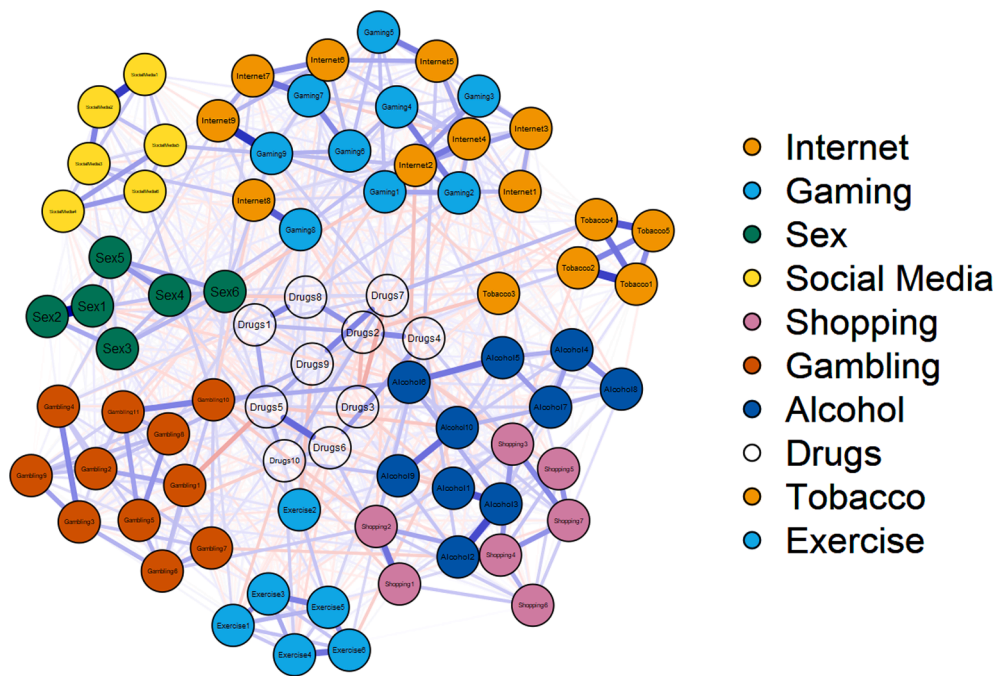


Fig. 1. Symptoms of addiction network. The 79 nodes represent symptoms of 10 forms of addiction, and edges represent EBIC-LASSO regularized partial correlations. Blue edges represent positive relationships and red edges represent negative relationships, with wider and more saturated edges representing stronger relationships. Nodes were labelled and colored according to the form of addiction they theoretically represent.

OGDQ-11 (*prioritized gambling over other areas*), OGDQ-6 (*feel guilty when gambling*), OGDQ-10 (*asked someone for money due to gambling*). This suggests that gambling related symptoms might increase the likelihood of activating symptoms of other addictive disorders. Interestingly however, the least influential symptoms were DAST-3 (*able to stop using drugs*), CDS-3 (*how soon after waking up you have a smoke*), and AUDIT-1 (*frequency of alcohol intake*).

Additionally, we calculated average centrality indices grouping symptoms by their corresponding disorders (see Table 3). Disorders arranged by descending centrality indices were ‘drugs’, ‘alcohol’, ‘online gaming’, ‘online gambling’, ‘internet use’, ‘sex’, ‘shopping’, ‘social media’, ‘exercise’, and ‘tobacco’.

3.3. Bridge symptoms

Following suggestions outlined in Vanzhula et al. (2021), we sought to identify bridge symptoms that may connect or serve as pathways between disorders. Specifically, we observed (i) bridge strength or the frequency of connections between symptoms across different disorders, and (ii) bridge expected influence or the sum of positive weighted edges across disorders. As seen in Fig. 3, bridge symptoms with the highest frequency of inter-disorder edges are DAST-1 (*used drugs for other than medical reasons*), DAST-4 (*had blackouts or flashbacks due to drug use*), and OGDQ-1 (*need to spend more and more money to get the desired high*). Additionally, bridge symptoms with the highest sum of positive weighted inter-disorder edges are DAST-1 (*used drugs for other than medical reasons*), DAST-5 (*feel guilty about drug use*), and DAST-2 (*abuse more than one drug at a time*).

3.4. Accuracy and stability of network

To assess the accuracy and stability of our network, we evaluated the edge-weight accuracy, centrality stability, and tested for significant differences across centrality indices. Firstly, the accuracy of the estimated edge-weights was evaluated with 95% bootstrapped CIs. Fig. 4 presents an illustration of the bootstrapped estimated edge-weight matrix including 95% CIs. The relatively sized bootstrapped CIs suggests

larger variability in estimation of edge weights, and thus implies a certain degree of bias. Specifically, larger CIs represent a larger ‘shaded area’ surrounding the mean bootstrapped estimated edge-weights (black line) and subsequently reduced confidence of ‘correct’ estimation of edge-weights between a set of two specific nodes (Epskamp et al., 2018). Therefore, interpretation of results presented here should be done with care. Secondly, we employed the case-dropping subset bootstrap to assess the stability of edge-weights and centrality indices. Fig. 5 panels C and D, present the correlation stability (CS) coefficient between original edge-weights and centrality indices obtained with 100% of sampled people and progressive sample subsets with incremental drop in % of cases. Epskamp et al. (2019) suggests that CS coefficients should not fall below 0.25 and preferably above 0.5 for meaningful inferences. Our network showed average correlations in edge-weights CS > 0.75 (Fig. 5. C), closeness CS > 0.5, and betweenness and strength CS above 0.25 and slightly below 0.5. Thus, emphasis of interpretation was placed on closeness.

3.5. Visual identification of network communities

Finally, we implemented an Exploratory Graphical Analysis (EGA) approach to ease interpretation of potential communities within our network analysis. We used the Walktrap community detection algorithm within an EBIC-glasso framework to identify the optimum number of dimensions that may be present in the network (Golino et al., 2020). The EGA and EBIC-glasso estimate similar networks; however, emphasis of interpretation in our network estimated with EGA-Walktrap is placed on identification of communities. As seen in Fig. 6, the optimal solution suggests that nine dimensions are sufficient to explain interrelations between symptoms of the ten forms of addictive behaviors, with internet abuse and online gaming merged into one single construct.

4. Discussion

The present study aspired to expand the understanding surrounding comorbidities between addictions, as well as the transition/replacement of one addiction form to/with another. To address this aim we

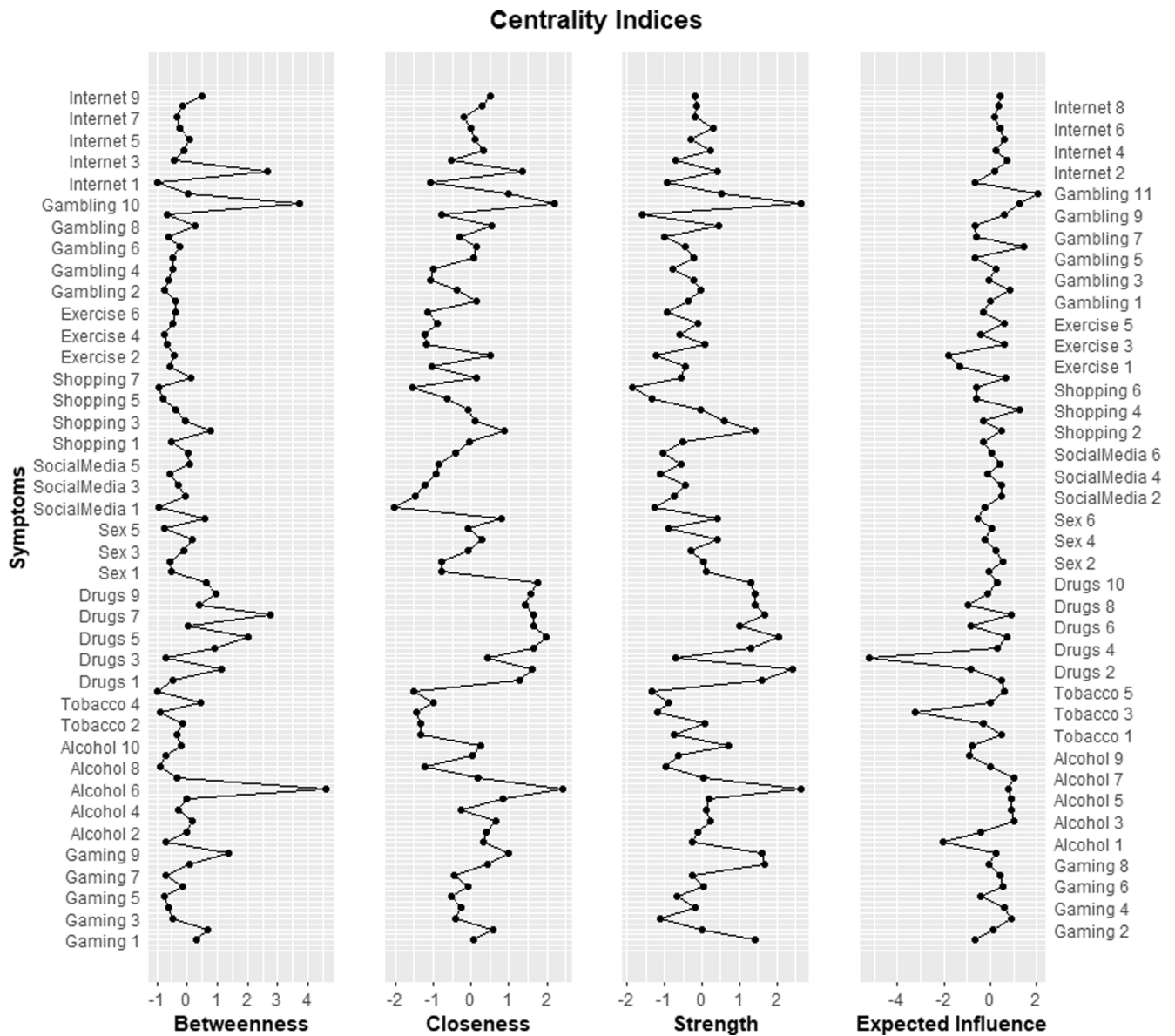


Fig. 2. Centrality indices. The horizontal axis represents standardized (Z) centrality. The vertical axis represents each symptom of addiction. Symptoms of addiction with higher centrality are further away (to the right) from the vertical axis.

Table 3
Centrality measures per variable.

Variable	Betweenness	Rank	Closeness	Rank	Degree	Rank	Expected influence	Rank	Overall	Rank
Gaming	-0.032	5	0.038	5	0.264	2	0.176	4	0.447	3
Alcohol	0.163	2	0.365	2	0.192	3	0.046	6	0.767	2
Tobacco	-0.373	9	-1.309	10	-0.817	9	-0.502	9	-3.002	10
Drugs	0.767	1	1.496	1	1.342	1	-0.535	10	3.072	1
Sex	-0.198	6	-0.100	6	-0.040	4	0.001	7	-0.337	6
Social Media	-0.294	8	-1.151	9	-0.859	10	0.178	3	2.127	8
Shopping	-0.244	7	-0.180	7	-0.334	7	0.082	5	0.676	7
Exercise	-0.545	10	-0.828	8	-0.536	8	-0.440	8	2.350	9
Gambling	-0.017	4	0.052	4	-0.104	5	0.403	1	0.334	4
Internet	0.108	3	0.084	3	-0.172	6	0.264	2	0.284	5

Note. ‘Overall’ represents the average of centrality indices. Additionally, variables were ranked according to centrality indices.

implemented an innovative Network Analysis (NA) approach, while using a large, adult, community sample to concurrently examine the network structure and associations of a broad range of addictive behavior symptoms. These captured addictive behaviors related to alcohol, drugs, tobacco, sex, online gambling, internet in general,

internet gaming, social media, shopping, and exercise. The resulting network structure demonstrated relatively acceptable stability and accuracy indices.

Overall, with the exception of disordered internet use and internet gaming disorder, findings indicate that all other forms of addictive

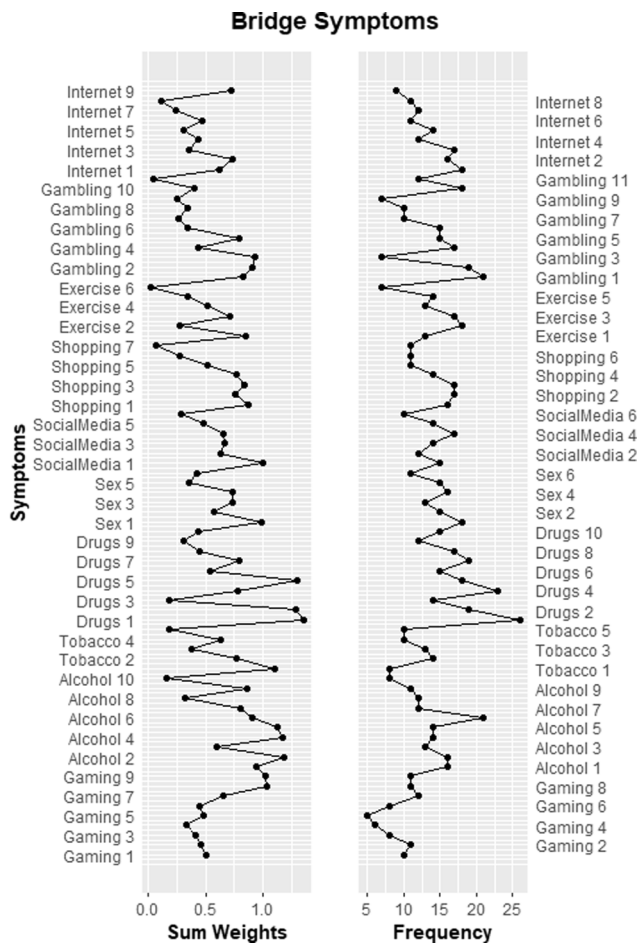


Fig. 3. Bridge symptom indices. The horizontal axis represents sums of weights and frequency of bridge symptoms across different forms of problematic behaviors. The vertical axis represents each symptom of different disorders.

behaviors assessed here are uniquely different. In other words, unique elements within each form of addiction provide evidence that justifies their classification as distinguishable addictive disorders, despite their overall similarities. Interestingly, particular symptoms related to gambling, drug and alcohol abuse displayed the highest levels of influence within the overall network of addictive behavior manifestations investigated. Of those, symptoms primarily related to drug abuse and disordered gambling were frequently and strongly connecting with other forms of addiction, increasing the potential likelihood of developing comorbidities or addiction substitution behaviors (i.e., bridge symptoms) between these disorders. As such, results may pose significant implications for the taxonomy, prevention, and treatment of addictive behaviors.

4.1. Taxonomy of addictive disorders

Overall, the web/network of the broad symptoms of addictive behaviors assessed was relatively sparse, with only 60% of symptoms showing connections with another symptom. Not surprisingly, most of these connections were observed between symptoms of the same addictive behaviour. Indeed, the strongest associations between pairs of symptoms usually represented activities that were conceptually related. For example, *feeling an urge to masturbate* and *using sex/masturbation to escape from personal problems* showed the strongest association compared to any other pair of symptoms assessed within the greater network.

The relative sparsity of connections underpinning the network of addiction behaviors' manifestations investigated reflects their

variability, despite the existence of common elements between the different addiction forms (Epskamp et al., 2018). From a diagnostic perspective, this reinforces their classification under a broader diagnostic umbrella of "addictive disorders/behaviors". Within this context, the strongest connections between manifestations of addictive behaviors were usually observed between symptoms of the same form of addiction. Indeed, this suggests that there are elements uniquely distinguishing the different forms of addictive behaviors assessed, potentially related to their different objects of interest (i.e., alcohol, substances, shopping etc.; Kendler et al., 2020).

This finding proposes that despite their inclusion within the same "family"/ diagnostic umbrella, these constitute different diagnostic entities/ disorders that do not necessarily co-exist in terms of their expressed behavior. Reinforcing this hypothesis, our community detection algorithm (Golino et al., 2020) identified nine clearly distinguishable forms of addictive behaviors including excessive online gambling (Griffiths, 1995), hypersexual activity (Carnes, 1983; Krueger, 2016), internet abuse and disordered gaming (Griffiths, 1995; Stavropoulos et al., 2019), social media abuse (Pontes et al., 2018), compulsive shopping (Andreassen et al., 2015), and compulsive exercise (Beck Lichtenstein & Jensen, 2016; Beck Lichtenstein et al., 2017).

Importantly, these findings are in line with a series of studies suggesting the need to recognize diverse forms of addiction/ problematic behaviors as specific disorders, rather than an overarching addiction diagnosis (Burleigh et al., 2019; Demetrovics & Griffiths, 2012; Griffiths, 1996; Griffiths, 2005; Wong et al., 2012). In other words, addictive disorders should be conceptualized as different sets of addiction symptoms that do not necessarily co-occur under a more diagnostically "loose" addiction entity (Borsboom & Cramer, 2013; van Borkulo et al., 2015). However, it is important to denote that disordered internet use and internet gaming behavior symptom networks mixed significantly, suggesting that further refinement in the conceptualization and differentiation between these different addictive behaviors is needed.

4.2. Central and bridge symptoms of addictive behaviors

Centrality indices were used to evaluate the relative importance of different symptoms of addictive behaviors within the broader network of behaviors examined (Epskamp et al., 2018; Hevey, 2018). In brief, these indices aimed to identify symptoms which could underpin addiction comorbidities, as well as addiction substitution or replacement. In this context, symptoms with more frequent connections and shortest paths included: *asked someone for money due to gambling*; *needed a first drink in the morning*; *abuse more than one drug at a time*; *guilt due to drug use*; and *neglect your family due to drug use*. These symptoms are related to disordered gambling, alcohol abuse and drug abuse, and present to have higher relative importance compared to other manifestations of addictive behaviors. Similarly, symptoms showing stronger associations (i.e., edge weights) included: *prioritized gambling over other areas*; *guilty when gambling*; and *asked someone for money due to gambling*. These symptoms are related to disordered gambling and are expected to exert greater influence on the network of symptoms of addictive behaviors. In other words, these symptoms are connected more frequently and more strongly with other presentations of addictive behaviors and may be seen as risk factors for exacerbating the negative impact of current symptomatology, while increasing the probability of developing further problematic behaviors, either in the context of comorbidities or substitution/replacement (Fried et al., 2017).

Indeed, centrality indices reflect the potential influence exerted on manifestations of addictive behaviors within and across other forms of addictive disorders (Hevey, 2018). However, focusing exclusively on symptoms associated with different forms of addiction enables the identification of *bridge symptoms* (Vanzhula et al., 2021). This is particularly useful to address influential symptoms (i.e., 'super spreaders') that might increase the likelihood of developing cross-addictive behaviors and/or developing a new form of addiction while

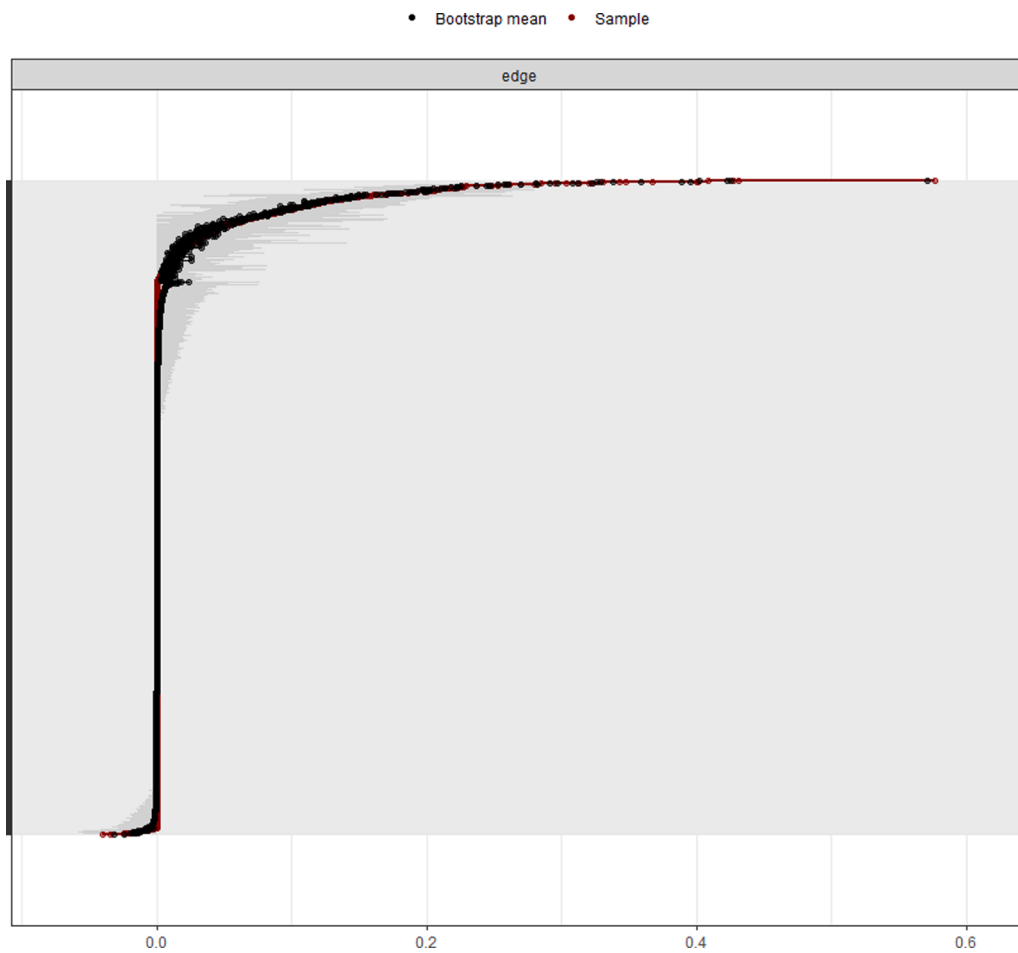


Fig. 4. Accuracy and stability of network presents the bootstrapped confidence intervals (CI) of estimated edge-weights. The x axis represents estimated edge-weights coefficients, and the y axis represents each estimated edge weight of the network ordered from the highest mean bootstrapped edge-weight to the lowest mean bootstrapped edge weight. Y axis labels have been removed to avoid cluttering. The red line indicates the sample values and the grey area the CI. The black line represents the mean bootstrapped estimated edge-weights.

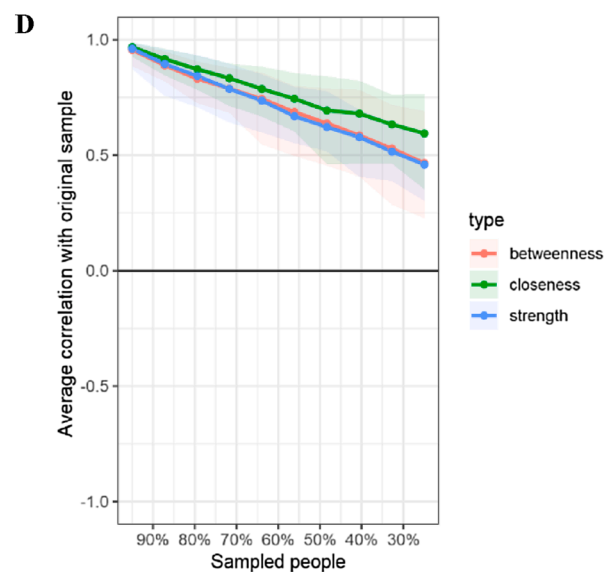
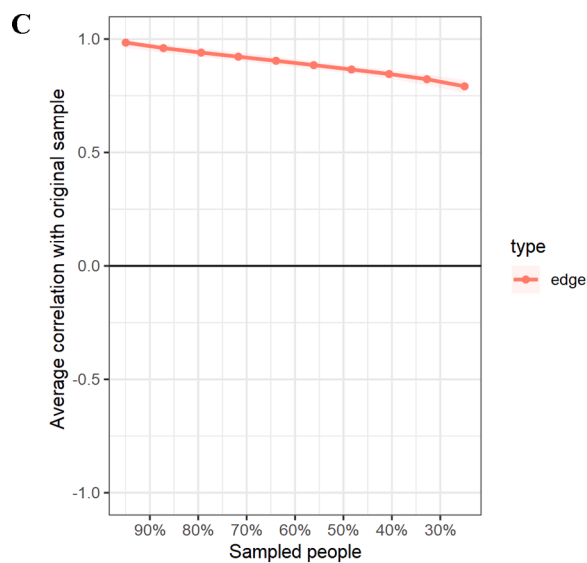


Fig. 5. Case-dropping subset bootstrap. Panel C and D present average correlations in edge weight (C) and centrality indices (D) between sampled people and each progressive incremental case-dropping subset.

disengaging from a previously established one.

Symptoms of addictive behaviors with the highest bridge centrality indices were predominantly associated with drug abuse (i.e., *used drugs for other than medical reasons, had blackouts or flashbacks due to drug use, feel guilty about drug use, and abuse more than one drug at a time*), and

disordered gambling (*need to spend more and more money to get the desired high*). This demonstrates that a variety of drug abuse related symptoms have the capacity to influence the development of comorbid addictions and/or seek alternative forms of addiction upon the extinction of the original addictive disorder (Haylett et al., 2004).

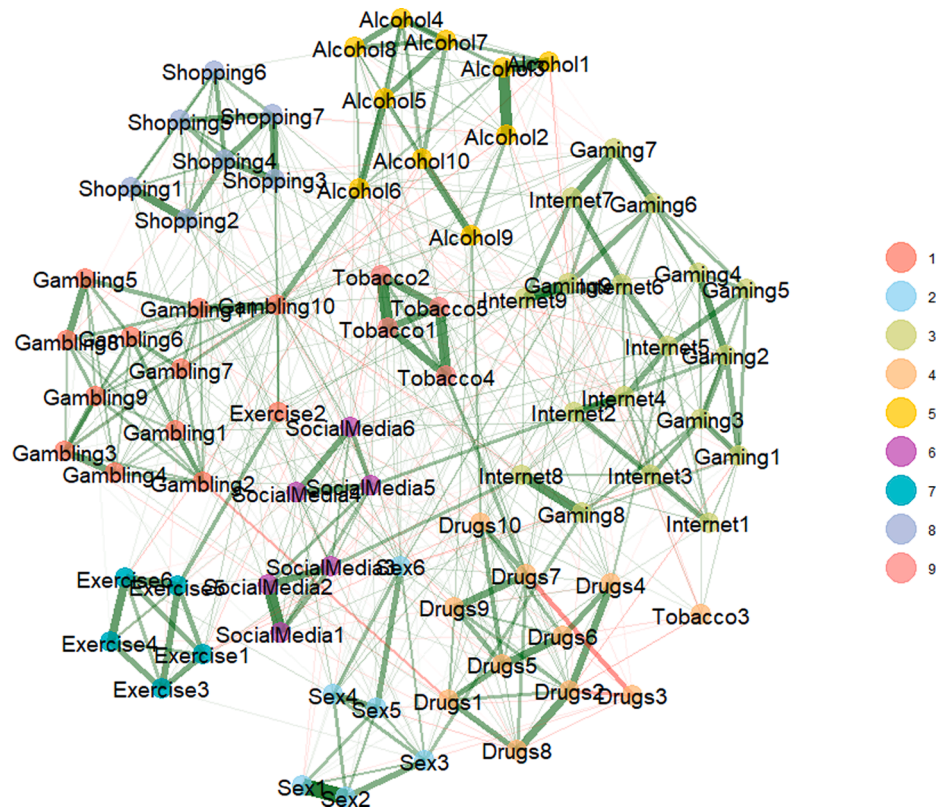


Fig. 6. Exploratory Graph Analysis (EGA) approach to detecting communities of problematic behaviors. As seen here, nine underlying communities of problematic behaviors present the optimum solution (with IGD and IDS overlapping as one dimension).

Counterintuitively, the least influential manifestations of addictive behaviors within the broader network may also convey valuable information. Specifically, the least influential symptoms observed in the current study included the perceived ability to exert control on the substance or activity of addiction (i.e., *able to stop using drugs; how soon after waking up you have a smoke; and frequency of alcohol intake*). This may mean that reduced perceived control and agency of one's addictive behavior is more a peripheral, and less a core element of their disorder (West & Brown, 2013).

Finally, observing centrality indices at the disorder level (e.g., disordered gaming) facilitates identification of potentially influential forms of addiction. Findings indicated that drug abuse was the most influential form of addiction followed by alcohol abuse. Interestingly however, the third most influential problematic behavior was gaming disorder (i.e., IGD; APA, 2013) denoting the importance of prioritizing the assessment of additional comorbidities when one presents with these particular addictive behaviors (Stavropoulos et al., 2019). Previous research supports this notion providing evidence of co-occurring forms of addiction including drugs, alcohol, and tobacco (Lorains et al., 2011); internet gaming, drugs and alcohol (Lee et al., 2018; Mérelle et al., 2017); internet gaming and gambling (Delfabbro & King, 2020); and sex and gambling (Farré et al., 2015). However, further investigation is warranted to replicate results reported in the present study.

4.3. Practical implications

Aside of the taxonomical implications highlighted above, our findings have practical implications in relation to the assessment and intervention protocols related to addictive disorders (Burleigh et al., 2019; Demetrovics & Griffiths, 2012; Griffiths, 1996; Griffiths, 2005; Griffiths, 2017). Firstly, considering assessment, the present study highlights the need for less broadly accepted forms of addictive problematic behaviors such as exercise, shopping, internet use and social

media to be separately assessed in clinical practice (Andreassen et al., 2015; Rozgonjuk et al., 2021; Stavropoulos et al., 2013; Trot et al., 2020). It is important to note, that some of the addictive behaviors analyzed in the current study are yet to be formally recognized as such (i.e., social media abuse, compulsive shopping, disordered internet use, and hypersexual activity).

Nonetheless, findings presented in the current study support the notion that different forms of addiction encompass uniquely different disorders (Anderson et al., 2017; Demetrovics & Griffiths, 2012; Griffiths, 1996; Kircaburun et al., 2020). Although all problematic behaviors may be assessed by an underlying common element (such as salience, mood modification, tolerance, withdrawal, conflict, and relapse; Griffiths, 2005), apparent differentiations pose the need for their independent assessment. This notion aligns with the inclusion of distinct forms of behavioral addictions such as disordered gambling and internet gaming disorder in the DSM-5 (APA, 2013). Overall, a more careful assessment of behavioral addictions which my often receive less attention in mental health practice, such as disordered social media use or problematic sexual behavior, would enable clinicians to diagnose individuals accordingly (Anderson et al., 2017; Griffiths, 1996; Stavropoulos et al., 2013).

Secondly, from an intervention perspective, evidence presented here highlights the importance of separately treating distinct symptoms/manifestations of addictive behaviors to avoid the development of comorbidities, as well as the transition from one form to another (Haylett et al., 2004). Specifically, our findings indicate that selected symptoms related to compulsive gambling, disordered drinking, and drug abuse (i.e., negative financial consequences, excessive preoccupation, guilt, and interpersonal strain due to the presence of the disordered behaviour) may pose a more significant risk for expanding one's addictive difficulties (Burleigh et al., 2019; Farré et al., 2015; Lee et al., 2018; Lorains et al., 2011; Martin et al., 2013a; Mérelle et al., 2017). Moreover, findings reported here suggest that symptoms related to

disordered drug use should be prioritized to minimize the likelihood of developing co-morbid forms of addiction (Nkansah-Amankra, 2020). Devising strategies to prioritize the treatment of these selected symptoms could also prove to be more effective in reducing the likelihood of replacing one form of addiction with another (Vanzhula et al., 2021).

5. Limitations, further research and conclusion

Results reported here need to be interpreted in the context of potentially significant limitations. Firstly, our sample is representative of adults living in developed countries and thus might not generalize to other individuals living in non-developed countries. Secondly, our sample is representative of non-clinically diagnosed individuals. Thus, further research might seek to reproduce these findings in individuals who have received a clinical diagnosis of addictive disorder(s). Thirdly, as our network structure showed only moderate stability and accuracy of edge weights, these results should be interpreted with some caution. Furthermore, network analysis assumes a formative approach to understanding addiction, thus relationships between symptoms and addictive disorders are perceived as causal systems (van Borkulo et al., 2015), however, as cross-sectional data has been employed here, causality cannot be assumed. Further research may wish to address this concern by employing longitudinal data collection, and thus enable analysis of directionality in edges between symptoms of addiction. Additionally, longitudinal datasets would enable the concurrent examination of both between and within individual differences, providing interesting clinical insights. Fourthly, considering the apparent differences in addictive behaviors across binary genders (i.e., males and females) and age groups, future work may wish to identify networks of addictive behaviors for these different groups. Fifthly, considering the potential association between problematic behaviors occurring exclusively in online environments, further studies may wish to employ measures that capture hypersexual behavior exclusively in online environments. Finally, further research should also investigate age-specific populations at risk for the development and establishment of addictive behaviors, such as children and emerging adults, to identify specific links/networks of comorbidities in relation to other highly prevalent disorders within these age-ranges.

Despite these limitations, our findings shed new light on the conceptualization and intervention of addictions. Using network analysis to a large population-based sample of adults, we provided important evidence justifying the need to further recognize unique forms of addiction. Additionally, we have provided evidence demonstrating the importance of addressing symptoms/manifestations of addictive behaviors related to drug abuse, disordered gambling, and disordered alcohol use as symptoms related to these addictive disorders may increase the likelihood of symptom severity, the development of comorbid addictions and/or the risk of substituting one form of addiction with another.

Ethical Standards – Animal Rights:

All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed consent:

Informed consent was obtained from all individual participants included in the study.

Confirmation Statement:

Authors confirm that this paper has not been either previously published or submitted simultaneously for publication elsewhere.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.abrep.2022.100406>.

References

- American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Author. doi: 10.1176/appi.books.9780890425596.
- Anderson, E. L., Steen, E., & Stavropoulos, V. (2017). Internet use and Problematic Internet Use: A systematic review of longitudinal research trends in adolescence and emergent adulthood. *International Journal of Adolescence and Youth*, 22(4), 430–454. <https://doi.org/10.1080/02673843.2016.1227716>
- Andreassen, C. S., Griffiths, M. D., Pallesen, S., Bilder, R. M., Torsheim, T., & Aboujaoude, E. (2015). The Bergen Shopping Addiction Scale, reliability and validity of a brief screening test. *Frontiers in Psychology*, 6(1374). <https://doi.org/10.3389/fpsyg.2015.01374>
- Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). The relationship between technological addictions and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychology of Addictive Behaviors*, 30(2), 252–262. <https://doi.org/10.1037/adb0000160>
- Andreassen, C. S., Pallesen, S., Griffiths, M. D., Torsheim, T., & Sinha, R. (2018). The Development and Validation of the Bergen-Yale Sex Addiction with a Large National Sample. *Frontiers in Psychology*, 9(144). <https://doi.org/10.3389/fpsyg.2018.00144>
- Beck Lichtenstein, M., & Jensen, T. T. (2016). Exercise addiction in CrossFit: Prevalence and psychometric properties of the Exercise Addiction Inventory. *Addictive Behaviors Reports*, 3, 33–37. <https://doi.org/10.1016/j.abrep.2016.02.002>
- Beck Lichtenstein, M., Emborg, B., Daugaard Hemmingsen, S., & Beck Hansen, N. (2017). Is exercise addiction in fitness centers a socially accepted behavior? *Addictive Behaviors Reports*, 6, 102–105. <https://doi.org/10.1016/j.abrep.2017.09.002>
- Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual review of clinical psychology*, 9, 91–121. <https://doi.org/10.1146/annurev-clinpsy-050212-185608>
- Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews*, 71, 252–266. <https://doi.org/10.1016/j.neubiorev.2016.08.033>
- Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews*, 104, 1–10. <https://doi.org/10.1016/j.neubiorev.2019.06.032>
- Brown, T., Stavropoulos, V., Christidi, S., Papastefanou, Y., & Matsa, K. (2021). Problematic internet use: The effect of comorbid psychopathology on treatment outcomes. *Psychiatry Research*, 298, Article 113789. <https://doi.org/10.1016/j.psychres.2021.113789>
- Burleigh, T. L., Griffiths, M. D., Sumich, A., Stavropoulos, V., & Kuss, D. J. (2019). A Systematic Review of the Co-occurrence of Gaming Disorder and Other Potentially Addictive Behaviors. *Current Addiction Reports*, 6, 383–401. <https://doi.org/10.1007/s40429-019-00279-7>
- Carnes, P. (1983). Out of the Shadows: Understanding Sexual Addiction. *CompCare*.
- Christensen, A. P., Golino, H., & Siliá, P. J. (2020). A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*, 34(6), 1095–1108. <https://doi.org/10.1002/per.2265>
- Cocco, K. M., & Carey, K. B. (1998). Psychometric Properties of the Drug Abuse Screening Test in Psychiatric Outpatients. *Psychological Assessment*, 10(4), 408–414. <https://doi.org/10.1037/1040-3590.10.4.408>
- Delfabbro, P., & King, D. L. (2020). Gaming-gambling convergence: Evaluating evidence for the ‘gateway’ hypothesis. *International Gambling Studies*, 20(3), 380–392. <https://doi.org/10.1080/14459795.2020.1768430>
- Demetrovics, Z., & Griffiths, M. D. (2012). Behavioral addictions: Past, present and future. *Journal of Behavioral Addictions*, 1(1), 1–2. <https://doi.org/10.1556/JBA.1.2012.1.0>
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195–212. <https://doi.org/10.1037/s13428-017-0862-1>
- Estévez, A., Jáuregui, P., Sánchez-Marcos, I., López-González, H., & Griffiths, M. D. (2017). Attachment and emotion regulation in substance addictions and behavioral addictions. *Journal of Behavioral Addictions*, 6(4), 534–544. <https://doi.org/10.1556/2006.6.2017.086>
- Etter, J.-F., Le Houezec, J., & Perneger, T. V. (2003). A Self-Administered Questionnaire to Measure Dependence on Cigarettes: The Cigarette Dependence Scale. *Neuropsychopharmacology*, 28, 359–370. <https://doi.org/10.1038/sj.npp.1300030>
- Farré, J. M., Fernández-Aranda, F., Granero, R., Aragay, N., Mallorquí-Bague, N., Ferrer, V., More, A., Bouman, W. P., ... Jiménez-Murcia, S. (2015). Sex addiction and gambling disorder: similarities and differences. *Comprehensive Psychiatry*, 56, 59–68. <https://doi.org/10.1016/j.comppsy.2014.10.002>

- Fleming, M. F., Barry, K. L., & McDonald, R. (1991). The Alcohol Use Disorders Identification Test (AUDIT) in a College Sample. *The International Journal of the Addictions*, 26(11), 1173–1185. <https://doi.org/10.3109/10826089109062153>
- Forbes, M. K., Wright, A. G. C., Markon, K. E., & Krueger, R. F. (2021). Quantifying the Reliability and Replicability of Psychopathology Networks Characteristics. *Multivariate Behavioral Research*, 56(2), 224–242. <https://doi.org/10.1080/00273171.2019.1616526>
- Ford, M., & Håkansson, A. (2020). Problem gambling, associations with comorbid health conditions, substance use, and behavioural addictions: Opportunities for pathways to treatment. *PLoS ONE*, 15(1). <https://doi.org/10.1371/journal.pone.0227644>
- Fried, E. I., van Borkulo, C. D., Cramer, A. O. J., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology*, 52, 1–10. <https://doi.org/10.1007/s00127-016-1319-z>
- Fuss, J., Briken, P., Stein, D. J., & Lochner, C. (2019). Compulsive sexual behavior disorder in obsessive-compulsive disorder: Prevalence and associated comorbidity. *Journal of Behavioral Addictions*, 8(2), 242–248. <https://doi.org/10.1556/2006.8.2019.23>
- Golino, H. P. (2021). EGAnet: Exploratory Graph Analysis – A framework for estimating the number of dimensions in multivariate data using network psychometrics. *R package*. <https://cran.r-project.org/web/packages/EGAnet/EGAnet.pdf>.
- Golino, H., Moulder, R., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Nesselroade, J., Sadana, R., Thiagarajan, J. A., & Boker, S. M. (2020). Entropy fit indices: New fit measures for assessing the structure and dimensionality of multiple latent variables. *Multivariate Behavioral Research*, 1–29. <https://doi.org/10.1080/00273171.2020.1779642>
- González-Cabrera, J., Machimbarrena, J. M., Beranuy, M., Pérez-Rodríguez, P., Fernández-González, L., & Calvete, E. (2020). Design and Measurement Properties of the Online Gambling Disorder Questionnaire (OGD-Q) in Spanish Adolescents. *Journal of Clinical Medicine*, 9(1). <https://doi.org/10.3390/jcm9010120>
- Griffiths, M. D. (1995). *Adolescent Gambling*. Routledge.
- Griffiths, M. D. (1996). Behavioural addiction: An issue for everybody? *Employee Counselling Today*, 8(3), 19–25. <https://doi.org/10.1108/13665629610116872>
- Griffiths, M. D. (2005). A ‘components’ model of addiction within a biopsychosocial framework. *Journal of Substance Use*, 10(4), 191–197. <https://doi.org/10.1080/14659890500114359>
- Griffiths, M. D. (2017). Behavioural addiction and substance addiction should be defined by their similarities not their dissimilarities. *Addiction*, 112, 1716–1724. <https://doi.org/10.1111/add.13828>
- Haylett, S. A., Stephenson, G. M., & Lefever, R. M. H. (2004). Covariation in addictive behaviours: A study of addictive orientations using the Shroter PROMIS Questionnaire. *Addictive Behaviors*, 29, 61–71. [https://doi.org/10.1016/S0306-4603\(03\)00083-2](https://doi.org/10.1016/S0306-4603(03)00083-2)
- Hevey, D. (2018). Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral Medicine*, 6(1), 301–328. <https://doi.org/10.1080/21642850.2018.1521283>
- JASP Team. (2020). JASP (Version 0.14.1) Computer Software. <https://jasp-stats.org>.
- Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M., Edman, J., Blaszczynski, A., Khazaal, Y., & Billieux, J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? *Addiction*, 112, 1709–1715. <https://doi.org/10.1111/add.13763>
- Kendler, K. S., Aggen, S. H., Werner, M., & Fried, E. I. (2020). A topography of 21 phobic fears: Network analysis in an epidemiological sample of adult twins. *Psychological Medicine*, 1–8. <https://doi.org/10.1017/S0033291720004493>
- Kim, H. S., Hodgins, D. C., Garcia, X., Ritchie, E. V., Musani, I., McGrath, D. S., & von Ranson, K. M. (2021). A systematic review of addiction substitution in recovery: Clinical lore or empirically-based? *Clinical Psychology Review*, *Epub ahead of print*. PMID, 34536796. <https://doi.org/10.1016/j.cpr.2021.102083>
- Kircaburun, K., Pontes, H. M., Stavropoulos, V., & Griffiths, M. D. (2020). A brief psychological overview of disordered gaming. *Current Opinion in Psychology*, 36, 38–43. <https://doi.org/10.1016/j.copsyc.2020.03.004>
- Krueger, R. B. (2016). Diagnosis of hypersexual or compulsive sexual behavior can be made using ICD-10 and DSM-5 despite rejection of this diagnosis by the American Psychiatric Association. *Addiction*, 111, 2107–2114. <https://doi.org/10.1111/add.13366>
- Lee, H. J., Tran, D. D., & Morrell, H. E. R. (2018). Smoking, ADHD, and problematic video game use: A structural modelling approach. *Cyberpsychology, Behavior, and Social Networking*, 00, 281–286. <https://doi.org/10.1089/cyber.2017.0429>
- Lorains, F., Cowlishaw, S., & Thomas, S. (2011). Prevalence of comorbid disorders in problem and pathological gambling: Systematic review and meta-analysis of population surveys. *Addiction*, 106, 490–498. <https://doi.org/10.1111/j.1360-0443.2010.03300.x>
- Martin, R. J., Usdan, S., Cremeens, J., & Vail-Smith, K. (2013a). Disordered gambling and co-morbidity of psychiatric disorders among college students: An examination of problem drinking, anxiety and depression. *Journal of Gambling Studies*, 30, 321–333. <https://doi.org/10.1007/s10899-013-9367-8>
- Martin, J., Cloutier, P. F., Levesque, C., Bureau, J. F., Lafontaine, M. F., & Nixon, M. K. (2013b). Psychometric properties of the functions and addictive features scales of the Ottawa Self-Injury Inventory: A preliminary investigation using a university sample. *Psychological assessment*, 25(3). <https://doi.org/10.1037/a0032575>
- Mérelle, S. Y. M., Kleiboer, A. M., Schotanus, M., Cluitmans, T. L. M., Waardenburg, C. M., Kramer, D., van de Mheen, D., & van Rooij, A. (2017). Which health-related problems are associated with problematic video-gaming or social media use in adolescents? A large-scale cross-sectional study. *Clinical Neuropsychiatry*, 14, 9–11.
- Montag, C., Bey, K., Sha, P., Li, M., Chen, Y. F., Liu, W. Y., Zhu, Y., Li, C., Markett, S., Keiper, J., & Reuter, M. (2015). Is it meaningful to distinguish between generalized and specific Internet addiction? Evidence from a cross-cultural study from Germany, Sweden. *Taiwan and China. Asia-Pacific Psychiatry*, 7(1), 20–26. <https://doi.org/10.1111/appy.12122>
- Montag, C., Wegmann, E., Sariyska, R., Demetrovics, Z., & Brand, M. (2021). How to overcome taxonomical problems in the study of Internet use disorders and what to do with “smartphone addiction”? *Journal of Behavioral Addictions*, 15(9), 908–918. <https://doi.org/10.1556/2006.8.2019.59>
- Montiel, I., Ortega-Barón, J., Basterra-González, A., González-Cabrera, J., & Machimbarrena, J. M. (2021). Problematic online gambling among adolescents: A systematic review about prevalence and related measurement issues. *Journal of Behavioral Addictions*, 10(3), 566–586. <https://doi.org/10.1556/2006.2021.00055>
- Müller, A., Loeber, S., Söchtig, J., Te Wildt, B., & De Zwaan, M. (2015). Risk for exercise, dependence, eating disorder pathology, alcohol use disorder and addictive behaviors among clients of fitness centres. *Journal of Behavioral Addictions*, 4(4), 273–280. <https://doi.org/10.1556/2006.4.2015.044>
- Müller, M., Brand, M., Mies, J., Lachmann, B., Sariyska, R. Y., & Montag, C. (2017). The 2D: 4D marker and different forms of internet use disorder. *Frontiers in Psychiatry*, 8, 213. <https://doi.org/10.3389/fpsy.2017.00213>
- Müller, M., & Montag, C. (2017). The Relationship Between Internet Addiction and Alcohol Consumption is Influenced by the Smoking Status in Male Online Video Gamers. *Clinical Neuropsychiatry*, 14(1), 34–43.
- Müller, A., Laskowski, N. M., Trotske, P., Ali, K., Fassnacht, D. B., de Zwaan, M., Brand, M., Häder, M., & Kyrios, M. (2021). Proposed diagnostic criteria for compulsive buying-shopping disorder: A Delphi expert consensus study. *Journal of Behavioral Addictions*, 10(2), 208–222. <https://doi.org/10.1556/2006.2021.00013>
- Nkansah-Amankra, S. (2020). Revisiting the Association Between “Gateway Hypothesis of Early Drug Use and Drug Use Progression: A Cohort Analysis of Peer Influences on Drug Use Progression Among a Population Cohort. *Substance Use & Misuse*, 55(6), 998–1007. <https://doi.org/10.1080/10826084.2020.1720245>
- Ostovar, S., Bagheri, R., Griffiths, M. D., & Hashima, I. H. M. (2021). Internet addiction and maladaptive schemas: The potential role of disconnection/rejection and impaired autonomy/performance. *Clinical Psychology & Psychotherapy*, 1–16. <https://doi.org/10.1002/cpp.2581>
- Pastor-Satorras, R., & Vespignani, A. (2001). Epidemic spreading in scale-free networks. *Physical Review Letters*, 86(14), 3200–3203. <https://doi.org/10.1103/PhysRevLett.86.3200>
- Petry, N. M., Zajac, K., & Ginley, M. K. (2018). Behavioral Addictions as Mental Disorders: To Be or Not to Be? *Annual Review of Clinical Psychology*, 14, 399–426. <https://doi.org/10.1146/annurev-clinpsy-032816-045120>
- Pontes, H. M., & Griffiths, M. D. (2016). The development and psychometric properties of the Internet Disorder Scale – Short Form (IDS9-SF). *Addicta: the Turkish Journal of Addictions*, 3(2). <http://doi.org/10.15805/addicta.2016.3.0102>
- Pontes, H. M., Talyor, M., & Stavropoulos, V. (2018). Beyond “Facebook Addiction”: The Role of Cognitive-Related Factors and Psychiatric Distress in Social Networking Site Addiction. *Cyberpsychology, Behavior, and Social Networking*, 21(4), 240–247. <https://doi.org/10.1089/cyber.2017.0609>
- Pontes, H., Schivinski, B., Sindermann, C., Li, M., Becker, B., Zhou, M., & Montag, C. (2021). Measurement and conceptualization of Gaming Disorder according to the World Health Organization framework: The development of the Gaming Disorder Test. *International Journal of Mental Health and Addiction*, 19, 508–528. <https://doi.org/10.1007/s11469-019-00088-z>
- Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*, 125(6), 747–757. <https://doi.org/10.1037/abn0000181>
- Rodrigues, F. A. (2019). Network Centrality: An Introduction. In E. Macau (Ed.), *A Mathematical Modeling Approach from Nonlinear Dynamics to Complex Systems* (pp. 177–196). Springer.
- Rozgonjuk, D., Sindermann, C., Elhai, J. D., Christensen, A. P., & Montag, C. (2020). Associations between symptoms of problematic smartphone, Facebook, WhatsApp, and Instagram use: An item-level exploratory graph analysis perspective. *Journal of Behavioral Addictions*, 9(3), 686–697. <https://doi.org/10.1556/2006.2020.00036>
- Rozgonjuk, D., Schivinski, B., Pontes, H. M., & Montag, C. (2021). Problematic Online Behaviors Among Gamers: The Links Between Problematic Gaming, Gambling, Shopping, Pornography Use, and Social Networking. *International Journal of Mental Health and Addiction*, 1–18.
- Schivinski, B., Brzozowska-Wóś, M., Stansbury, E., Satel, J., Montag, C., & Pontes, H. (2020). Exploring the Role of Social Media Use Motives, Psychological Well-Being, Self-Esteem, and Affect in Problematic Social Media Use. *Frontiers in Psychology*, 11, 617140. <https://doi.org/10.3389/fpsyg.2020.617140>
- Sixto-Costoya, A., Castelló-Cogollos, L., Alexandre-Benavent, R., & Valderrama-Zurián, J. C. (2021). Global scientific production regarding behavioral addictions: An analysis of the literature from 1995 to 2019. *Addictive Behaviors Reports*, 14, Article 100371. <https://doi.org/10.1016/j.abrep.2021.100371>
- Skinner, H. A. (1982). The Drug Abuse Screening Test. *Addictive Behaviors*, 7, 363–371. [https://doi.org/10.1016/0306-4603\(82\)90005-3](https://doi.org/10.1016/0306-4603(82)90005-3)
- Stavropoulos, V., Alexandraki, K., Motti-Stefanidi, F. (2013). Recognizing internet addiction: Prevalence and relationship to academic achievement in adolescents enrolled in urban and rural Greek high schools. *Journal of Adolescence*, 2013, 36(3), 565–576. doi: 10.1016/j.adolescence.2013.03.008.
- Stavropoulos, V., Gomez, R., Steen, E., Beard, C., View, L., & Griffiths, M. D. (2017). The longitudinal association between anxiety and Internet addiction in adolescence: The moderating effect of classroom extraversion. *Journal of Behavioral Addictions*, 6(2), 237–247. <https://doi.org/10.1556/2006.6.2017.026>

- Stavropoulos, V., Gomez, R., & Motti-Stefanidi, F. (2019). Internet Gaming Disorder: A Pathway Towards Assessment Consensus. *Frontiers in Psychology*, *10*, 1822. <https://doi.org/10.3389/fpsyg.2019.01822>
- Szabo, A., Griffiths, M. D., Høglid, R. A., & Demetrovics, Z. (2018). Drug, nicotine, and alcohol use among exercisers: Does substance addiction co-occur with exercise addiction? *Addictive Behaviors Reports*, *7*, 26–31. <https://doi.org/10.1016/j.abrep.2017.12.001>
- Tang, K. T. Y., Kim, H. S., Hodgins, D. C., McGrath, D. S., & Tavares, H. (2020). Gambling disorder and comorbid behavioral addictions: Demographic, clinical, and personality correlates. *Psychiatry Research*, *284*. <https://doi.org/10.1016/j.psychres.2020.112763>
- Terry, A., Szabo, A., & Griffiths, M. D. (2004). The Exercise Addiction Inventory: A New Brief Screening Tool. *Addiction Research & Theory*, *12*(5), 489–499. <https://doi.org/10.1080/16066350310001637363>
- Trot, M., Jackson, S. E., Firth, J., Jacob, L., Grabovac, I., Mistry, A., Stubbs, B., & Smith, L. (2020). A comparative meta-analysis of the prevalence of exercise addiction in adults with and without indicated eating disorders. *Eating and Weight Disorders – Studies on Anorexia, Bulimia and Obesity*, *26*, 37–46. <https://doi.org/10.1007/s40519-019-00842-1>
- Van Borkulo, C., Boschloo, L., Borsboom, D., Penninx, B. W. J. H., Waldrop, L. J., & Schoevers, R. A. (2015). *JAMA Psychiatry*, *72*(12), 1219–1226. <https://doi.org/10.1001/jamapsychiatry.2015.2079>
- Van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3), 1–67. <https://www.jstatsoft.org/v45/i03/>.
- Van Rooij, A. J., Van Looy, J., & Billieux, J. (2017). Internet Gaming Disorder as a formative construct: Implications for conceptualization and measurement. *Psychiatry and Clinical Neurosciences*, *71*, 445–458. <https://doi.org/10.1111/pcn.12404>
- Vanzhula, I. A., Kinkel-Ram, S. S., & Levinson, C. A. (2021). Perfectionism and Difficulty Controlling Thoughts Bridge Eating Disorder and Obsessive-Compulsive Disorder Symptoms: A Network Analysis. *Journal of Affective Disorders*, *283*, 302–309. <https://doi.org/10.1016/j.jad.2021.01.083>
- West, R., & Brown, J. (2013). *Theory of Addiction (2nd Ed.)*. Addiction Press.
- Wong, T. W., Reid, R. C., & Parhami, I. (2012). Behavioral Addictions: Where to Draw the Lines? *Psychiatric Clinics of North America*, *35*(2), 279–296. <https://doi.org/10.1016/j.psc.2012.03.001>
- World Health Organization (2021). *ICD-11 International Classification of Diseases 11th Revision*. Retrieved on 22/12/2021 by <https://icd.who.int/en#:~:text=ICD%2D11,Diseases%2011th%20Revision>.
- Xu, L., Nan, J., & Lan, Y. (2020). The Nucleus Accumbens: A Common Target in the Comorbidity of Depression and Addiction. *Frontiers in Neural Circuits*, *14*. <https://doi.org/10.3389/fncir.2020.00037>
- Yang, Z., Algesheimer, R., & Tessone, C. J. (2016). A Comparative Analysis of Community Detection Algorithms on Artificial Networks. *Scientific Reports*, *6* (30750). <https://doi.org/10.1038/srep30750>