Co-occurrence of common biological and behavioral addictions: using network analysis to identify central addictions and their associations with each other

International Journal of Mental Health and Addiction
https://doi.org/10.1007/s11469-022-00995-8

ORIGINAL ARTICLE

Co-occurrence of Common Biological and Behavioral Addictions: Using Network Analysis to Identify Central Addictions and Their Associations with Each Other

Rapson Gomez[1] · Taylor Brown[2] · Deon Tullett-Prado[2] · Vasileios Stavropoulos[2,3]

Accepted: 17 December 2022

Abstract
The present study used network analysis to examine the network properties (network graph, centrality, and edge weights) comprising ten different types of common addictions (alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet use) controlling for age and gender effects. Participants ($N=968$; males = 64.3%) were adults from the general community, with ages ranging from 18 to 64 years (mean = 29.54 years; $SD=9.36$ years). All the participants completed well-standardized questionnaires that together covered the ten addictions. The network findings showed different clusters for substance use and behavioral addictions and exercise. In relation to centrality, the highest value was for internet usage, followed by gaming and then gambling addiction. Concerning edge weights, there was a large effect size association between internet gaming and internet usage; a medium effect size association between internet usage and social media and alcohol and drugs; and several small and negligible effect size associations. Also, only 48.88% of potential edges or associations between addictions were significant. Taken together, these findings must be prioritized in theoretical models of addictions and when planning treatment of co-occurring addictions. Relatedly, as this study is the first to use network analysis to explore the properties of co-occurring addictions, the findings can be considered as providing new contributions to our understanding of the co-occurrence of common addictions.

Keywords Addictions · Co-occurrence · Network analysis · Centrality · Edge weights

An addiction is an ongoing failure to resist an impulse or urge to engage in a certain response, despite experiencing repeated harm from such engagement (American Society of Addiction Medicine, 2019; Grant et al., 2010; Kardefelt-Winther et al., 2017). Apart from the more commonly recognized psychoactive substance use (e.g., alcohol, drugs [e.g.,

This manuscript includes original work not previously published or presented and not under current review elsewhere. All data has been made publicly available with the publication. The study was not preregistered.

✉ Taylor Brown
Taylor.Brown@live.vu.edu.au

Extended author information available on the last page of the article

Published online: 17 January 2023

opiates and hallucinogens], and nicotine or cigarette smoking), non-substance behaviors, such as gambling (online or offline), gaming, eating, sex, exercise, shopping, internet use, internet gaming, social media use, and work (collectively referred to as "behavioral"), have been proposed as having the propensity for an addiction (Brown et al., 2021; Griffiths, 2005; Rozgonjuk et al., 2021; Sussman et al., 2011). Additionally, existing evidence indicates high co-occurrence of these different addictions (Brown et al., 2021; Charzyńska et al., 2021; Marmet et al., 2019; Sussman et al., 2011; Sussman & Arnett, 2014; Konkolÿ Thege et al., 2016; Reer et al., 2021; Richter et al., 2017). Indicatively, a systematic literature review by Burleigh et al. (2019) supported that disordered gaming significantly co-occurred with the abuse of caffeine, tobacco, alcohol, and cannabis use. Similarly, Ford & Håkansson (2020) examined an adult Swedish sample and concluded significant links between problem gambling and tobacco use, problematic shopping, and problem gaming, while Schluter et al. (2018) studied a large Canadian sample to reveal correlations between alcohol, tobacco, cannabis, cocaine, gambling, shopping, video gaming, over-eating, sexual activity, and over-working addictive behaviors. Related to this, as there is much overlap in the etiological, phenomenological, clinical presentations, and genetic vulnerabilities of these addictions, it has been proposed that these addictions reflect a dimensional spectrum of interrelated conditions. Expressed differently, the different addictions are different manifestations of the same underlying addiction disorder (Kim & Hodgins, 2018; Marmet et al., 2018, 2019; Shaffer et al., 2004). Thus, the different addictions can be considered a group of related disorders belonging to the same overarching disorder, with varying circumstances giving rise to unique manifestations or different addictions (Perales et al., 2020).

To date, and given the dimensional model proposed for the co-occurrence of different addictions, the associations of the various addictions have been examined using various latent variable frameworks, such as factor analysis. As applied to the co-occurrence of different addictions, a latent variable model generally assumes the existence of a general addiction factor (unobservable) that causes a range of addictions. For a large group of adults involving half the sample of participants as in the current study, Gomez et al. (2022) used exploratory factor analysis (EFA) to examine the factor structure of a model with three psychoactive substance addictions (alcohol use, cigarette smoking, and substance use) and seven behavioral addictions (sex, social media use, shopping, exercise, online gambling, internet gaming, and internet use). The findings supported a two-factor model, with different factors for the psychoactive substance and behavioral addictions (excluding exercise addiction). A subsequent confirmatory factor analysis (EFA) with the other half of the sample supported the two-factor model. Also, for the entire sample, they were good support for the reliability and concurrent and discriminant validities of the two latent factors. Additionally, apart from the associations for cigarette smoking with gaming and social media, exercise with alcohol and drugs (undifferentiated), and online gambling and internet, all the other associations were positively and significantly correlated with each other.

More recently an alternate approach called network analysis has been proposed for examining and understanding psychopathology (Borsboom & Cramer, 2013). In the network approach, the set of variables in the model (such as the symptoms of a disorder) is viewed as a causal system, which interacts with each other in meaningful ways, resulting in the disorder (Borsboom & Cramer, 2013). As applied to a group of co-occurring addictions, a network model would therefore reflect the different addictions interacting with each other in meaningful ways. Despite the current wide use of network analysis for extending our understanding of many clinical disorders, to date, the network approach has not been used for understanding co-occurring addictions. This was examined in the current study for the same group of participants and the same set of common addictions (alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet use addictions) as in our previous study, cited earlier (Gomez et al., 2022). Using the same participants and addictions was considered advantageous as this could allow a comparison of the current network findings with the previous factor analysis findings that are not confounded by the participants, questionnaire, and procedural differences.

Network Analysis

Network models are tested using network analysis (Borsboom & Cramer, 2013; Boschloo et al., 2015). In a network model, the variables are referred to as nodes, and the connections between variables are referred to as edge weights. Generally, in network analysis, partial correlations between pairs of variables are estimated, controlling for all other variables in the model. Markov random fields (Epskamp et al., 2018), with regularization, are used to compute the partial correlations in most network models. This means that the analysis will show only the more important associations or edges between pairs of variables (Borsboom & Cramer, 2013; von Klipstein et al., 2021). Therefore, the associations between the variables in a network analysis can be expected to differ from that obtained using correlations and multiple regression analyses (Epskamp et al., 2017). Network analysis is also advantageous over structural equation modeling (SEM) as no equivalent undirected models can be modeled (Epskamp et al., 2017).

In addition to edge weights, there are other findings in network analysis that are not available from correlation, multiple regression analysis, and SEM. Two of the more frequently reported results are network graphs and centrality values. The network graph (figures) produced by network analysis provides a very intuitive way to visualize the co-occurrence or associations of the variables in the model (Bringmann & Eronen, 2018). The centrality values of the variables in the model can be used to examine their relative influence and importance of the different variables. A node (i.e., variable) with a high centrality value is highly connected to other nodes in the model, and therefore, it is more influential or important than the other nodes with lower centrality values. Traditionally, the influence of a set of related variables is viewed in terms of their mean scores, with higher scores interpreted as more influential. Means scores are different from their network-based centrality values; specifically, mean levels of variables can change without changes in their centrality values (Yang et al., 2016). Therefore, network analyses could indicate a different conclusion about the relative influence of the variables in the model, compared to their mean scores (Mullarkey et al., 2019). Thus, the network approach will enable further understanding of the central and influential addictions beyond just mean scores. Given the network connectivity characteristics of the network nodes, and as the symptom with the highest centrality value is considered being most influential, it follows that it will have more influence than the other nodes on influencing the network as a whole, and consequently, intervening on this node can be expected to spread to other nodes and maximize the impact of an intervention.

Overall, concerning a network analysis of addiction variables, the results from a network analysis of co-occurring addictions will reveal new findings, such as the relative influence (important) of the different addictions in the model, and the uniqueness and strengths of the associations between the different addictions in the model, controlling for all other variables in the network model. Despite the noted advantages that network analysis can offer for a better and extended understanding of different co-occurring addictions, as far we are aware, this approach has not been applied to co-occurring addictions as a group in only two studies (Rozgonjuk et al., 2021; Zarate et al., 2022). Rozgonjuk et al. (2021) used network analysis to examine the interrelations between several addictions involved in online activities. For the same group of participants and addictions as in this study, Zarate et al. (2022) applied network analysis to examine the central addictions and/or the important associations between the different addictions. Thus, their findings are directly related to the current study. Their findings for centrality showed the highest centrality for gambling followed in sequence by internet use, internet gaming, alcohol, shopping, social media use, drugs (undifferentiated), sex, smoking, and exercise. Also, there were positive associations across different addictions. However, this study as well as the Rozgonjuk et al. study had some limitations. In both studies, the network analysis in their study included all the items (symptoms) in the relevant measures and not just the addiction constructs. Therefore, it inferred the central addictions and/or the important associations between the different addictions indirectly by considering the symptoms comprising the different addictions. Procedurally, this could have involved a high degree of subjectivity. Relatedly, the use of all the items in the different addiction questionnaires in the Zarate et al. study resulted in 79 nodes, making what is already subjective judgment even more difficult and problematic. In contrast to applying network analysis at the item level, applying it for 10 addiction constructs would mean far fewer nodes (i.e., only 10) in the model, and more direct data on the central addictions and the important associations between the different additions at the construct level, and therefore, more easily interpretable evaluation of the co-occurrence of the different addictions than using all the symptoms comprising the ten addictions.

Aims of the Current Study

Given the omissions and limitations in the existing findings in understanding addictions co-occurring in a group, the current study used network analysis to examine the major network properties (i.e., network graph, centrality, and edge weights) of a network model involving ten different types of addictions. The addictions were alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet use. Age and gender were controlled in the network analyses as they are known to influence different addiction types (e.g., Andreassen et al., 2013; Becker & Chartoff, 2019; Becker et al., 2017; Cotto et al., 2010; Roberts et al., 2021; Thege et al., 2015).

Given that there is now some level of acceptance that the different addictions have considerable overlap in their etiological, phenomenological, clinical presentations, and genetic vulnerabilities (Brand et al., 2019; Burleigh et al., 2019; Kotyuk et al., 2020; Sussman et al., 2011; Sussman & Arnett, 2014; Zarate et al., 2022) and that they are likely to represent a different manifestation of the same underlying disorder (Kim & Hodgins, 2018; Marmet et al., 2018, 2019; Shaffer et al., 2004), it speculated that there would be considerable overlap across the addictions, and therefore, their intercorrelations can be expected to be at least moderately high. However, as this study is exploratory and as there has been no previous network study of co-occurring addictions at the construct level, no specific predictions are made.

Method

Participants

There were 968 English-speaking adult participants from the community. Their age ranged from 18 to 64 years (mean = 29.54 years; $SD = 9.36$ years). There were 622 males (64.3%; mean age = 29.46 years, $SD = 8.93$ years), 315 females (32.5%; mean age = 30.02 years, $SD = 10.39$ years), and 31 participants identified as queer/trans-non-binary/other (3.2%; mean age = 26.26, SD = 5.13). No significant age variations occurred between the three groups [$F(5, 962) = 1.489$, $p = 0.191$], as well as between men and women only [t (935) = 0.846, $p = 0.398$]. Slightly more than half the participants reported being employed (55.0%), and most of them reported having completed at least secondary education (98.2%; see Table 1 for detailed socio-demographics).

Table 1 Socio-demographic information of the sample

Variables	Frequency ($N = 968$)	Valid percentage (%)
Ethnicity background		
African American	55	5.7
Caucasian	595	61.5
Asian	184	19
Hispanic/Latino	46	4.8
Other	88	9
Education		
Other tertiary education	185	19.1
High school or equivalent	251	25.9
TAFE	85	8.8
Undergraduate education	218	22.5
Postgraduate education	200	20.6
Other	29	3.1
Marital status		
Single	592	61.2
Living with another person	137	14.2
Married	188	19.4
Divorced	20	2.1
Other	31	3.1
Employment		
Full-time	331	34.2
Part-time	111	11.5
Causal	23	2.4
Self-employed	67	6.9
Unemployed	187	19.3
Full-time students	141	14.6
Other	103	11.1

Measures

Demographic

Demographic information on age, gender, employment, and education levels was obtained as part of the questionnaires completed.

Addictions

Scores for the 10 different types of addictions included in the study (alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet) were obtained using well-developed, theoretical-based, and psychometrically sound addiction-specific questionnaires, as presented in Table 2. The table also includes the internal consistency reliability coefficients (Cronbach α values) for these measures in the current study.

Procedure

The Human Ethics Research Committee of Victoria University (Australia) approved the study. The study was advertised widely, adopting a non-random sampling procedure. The survey was conducted online. Interested participants were invited to register for the study via a Qualtrics link available on social media (i.e., Facebook, Instagram, Twitter), the Victoria University websites, and digital forums (i.e., reddit.com). The link took them to the Plain Language Information Statement (PLIS), and interested individuals were directed to click a button to agree to informed consent. This was followed by the questions seeking socio-demographic information and the study questionnaires for addictions.

Statistical Procedure

Corresponding to the aim of the current study, the model for network analyses included the 10 addictions (alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet usage). According to Epskamp and Fried (2018), the number of participants must exceed the number of estimated parameter variables. With 10 nodes in the network, the total number of estimated parameters in this model was 66 $[(11)+(10\times 11/2)]$ (Leme et al., 2020). As our sample size was 968, our sample size was deemed sufficient for our network analysis.

To conduct the network analyses in the current study, the network module available in Jeffreys' Amazing Statistics Program (JASP) version 0.14.1.0 was used (JASP Team, 2020). In this program, the R package for bootnet is used to conduct the network analyses (Epskamp et al., 2018), and the qgraph is used to conduct network graphs (Epskamp et al., 2012). The Least Absolute Shrinkage and Selection Operator or g-lasso is used in the network (Tibshirani, 1996), which produces regularized partial correlation, thereby producing the optimal degree of shrinkage according to an EBIC and a hyperparameter (set at 0.5 in the study; Epskamp & Fried, 2018; Foygel & Drton, 2010). Consequently, the network produced a model that is sparser and easier to interpret.

Table 2 Questionnaires used in the current study for measuring different addictions

Addiction	Questionnaire used	Brief description	Example of an item	α
Shopping	Bergen Shopping Addiction Scale (BSAS; Andreassen et al., 2015)	7 shopping addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	I shop/buy things in order to change my mood	.88
Social Media Use	Bergen Social Media Use Addiction Scale (BSMAS; Andreassen et al., 2012)	6 social media use addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	Felt an urge to use social media more and more	.88
Sex	Bergen–Yale Sex Addiction Scale (BYSAS; Andreassen et al., 2012)	6 sex addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	Felt an urge to masturbate/have sex more and more	.84
Exercise	Revised Exercise Addiction Inventory (EAI-R; Szabo et al., 2019)	6 exercise addiction symptoms being experienced; 6-point scale (higher scores = more severity)	Exercise is the most important thing in my life	.84
Gambling	Online Gambling Disorder Questionnaire (OGD-Q); González-Cabrera et al., 2020)	11 online gambling addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	Have you tried to control, reduce, or stop gambling and have not been able to do so?	.94
Internet Gaming	Internet Gaming Disorder Scale – Short-Form (IGDS9-SF; Pontes & Griffiths, 2015)	9 internet gaming addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	Do you feel more irritability, anxiety, or even sadness when you try to either reduce or stop your gaming activity?	.89
Internet	Internet Disorder Scale–Short Form (IDS9-SF; Pontes & Griffiths, 2016)	9 internet addiction symptoms experienced during the past 12 months; 5-point scale (higher scores = more severity)	Do you feel preoccupied with your online behavior?	.90
Alcohol	Alcohol Use Disorders Identification Test (AUDIT; Babor, de la Fuente, Sauders, & Grant, 1992)	10 alcohol addiction symptoms being experienced; 5-point scale (higher scores = more severity)	During the past year, how often have you felt guilt or remorse after drinking?	.89
Drugs	Drug Abuse Screening Test (DAST-10; Skinner, 1982)	10 drugs addiction symptoms experienced during the past 12 months; yes/no response (higher scores = more severity)	Are you unable to stop abusing drugs when you want to?	.78
Cigarette	Cigarette Dependence Scale – 5 (CDS-5; Etter et al., 2003)	5 cigarette addiction symptoms being experienced; 5-point scale (higher scores = more severity)	After a few hours without smoking, I feel an irresistible urge to smoke	.68

As mentioned in the Introduction, a network analysis produces a network graph which is a visualization of the data structure, estimates of the centrality of the nodes, and edge weight values between the nodes. In the network graph, the distance between nodes is indicative of the relationship, with more similar nodes being closer to each other. Also, blue edges indicate positive relations, red edges indicate negative relations, and thickness and more color denser lines indicate stronger relationships. Additionally, when the network analysis applies Fruchterman and Reingold's (1991) algorithm to position the nodes (as is the case in the current study), the positioning of the nodes is such that the nodes with stronger correlations are near the center, whereas the nodes with weaker correlations are more to the periphery of the network. All of these make the interpretation of the network easier.

The commonly reported indices of centrality are betweenness, closeness, degree (strength), and expected influence (Bringmann et al., 2019; Opsahl et al., 2010). Although all four centrality indices are reported, the focus will be on the degree (referred to as strength in a weighted network, as is the case in the current study) for ascertaining the centrality of the nodes as it is known to reflect reasonably precise centrality estimates for psychology networks (Santos et al., 2018). In brief, the strength of a node is the sum of all direct associations a given symptom exhibits with all other nodes, with higher values indicating more centrality. In a network, the presence of an edge between two nodes (independent of its coefficient values) indicates that the pairs of variables in question are significantly correlated with each other, controlling for the other nodes in the network, whereas the absence of an edge between two nodes indicates that they are not significantly correlated with each other, controlling for the other nodes in the network. Based on guidelines proposed by Christensen and Golino (2021), we interpreted the effect sizes of the edge weights as follows: negligible ≤ 0.14, small $= \geq 0.15$ to < 0.25, moderate ≥ 0.25 to < 0.35, and large ≥ 0.35 (Christensen & Golino, 2021). For the current study, we considered associations with large and moderate effect sizes to be worthy of note and interpretation, and associations that were small and negligible were not important and not worthy of interpretation.

Researchers have pointed out that to have confidence in centrality and edge findings obtained in our network analysis, the network findings must also be evaluated for their accuracy and stability (i.e., the likelihood that the network results will be replicated). The accuracy of the edge weights can be evaluated using bootstrap 95% non-parametric confidence intervals (CIs), with narrower CIs suggesting a more precise estimation of the edge (Epskamp et al., 2018). When the CIs around most of the estimated edge weights are large, it means that they are likely not to differ significantly from each other, and therefore interpreting the order of most edges in the network could be problematic and has to be done with care. Concerning the stability of the centrality indices, bootstrapping referred to as case-dropping can be used (Epskamp & Fried, 2018). This procedure quantifies in terms of correlation stability coefficients if the order of centrality indices remains the same after re-estimating the network with fewer cases. Although a correlation stability coefficient of 0.7 or higher is desired, Epskamp et al. (2018) have suggested that correlation stability coefficient values above 0.5 are acceptable. For the current study, we used these bootstrap procedures for evaluating the accuracy and stability of edge weights and centrality. Both were estimated with 1000 bootstraps.

Results

Missing Values and Descriptives

As mentioned earlier, there were 968 participants in the study. The number and the percentages of missing values across the 12 variables in the study are shown in Supplementary Table S1. As the percentages of missing values for the variables ranged between 0 and 1.7%, they can be considered negligible. In the network analysis, missing data were handled using the "exclude pairwise method."

Supplementary Table S1 also includes the mean and standard deviation scores for all the addictions. As shown, the addictions with the top three mean scores were internet usage (mean = 19.96), followed by gaming (mean = 18.15), and then exercise (mean = 14.37), and the addictions with the lowest mean scores were drug use (mean = 1.69) that followed alcohol use (mean = 4.47).

Network Analysis

For the network, there were 12 nodes (10 addictions, age, and gender) and therefore the potential number of edges that would be estimated was 66. However, given the EBIC glasso estimation applied in the study, the number of edges estimated was reduced to 43 (sparsity = 0.35).

Visualization of the Network

A visualization of the relationship of nodes (addictions) in the network is shown in Fig. 1. As shown in the figure, substance use addictions including alcohol, cigarette smoking, and drug use (1 to 3 in the figure) were clustered together in one section of the network. Except for exercise, all the other behavioral addictions (4 to 9 in the network) were positioned in a different section of the network. Exercise (10 in the figure) was positioned by itself separately from all the other addictions.

Centrality of the Nodes in the Network

Table 3 shows the centrality of the nodes in the network. Figure 2 shows this graphically. As will be noticed in Table 3 and Fig. 2, the strength centrality index (used in the study to ascertain centrality) was highest for internet usage followed by gaming use and then gambling. They were lowest for exercise which was just below cigarette smoking.

Edge Weights in the Network

Table 4 shows the weight matrix between these nodes. As shown in Table 4, there was a large effect size association between gaming and internet use; a medium effect size association between alcohol and drugs (undifferentiated) and internet use and social media; and small effect size associations for cigarette smoking and drugs (undifferentiated), alcohol and gambling, gaming and gambling, gambling and shopping, social media, and shopping. There were also negligible effect size associations for alcohol with cigarette smoking and sex, cigarette smoking with shopping, drugs (undifferentiated), with gambling and internet use, gaming with sex, gambling with sex and exercise, internet with sex and shopping,

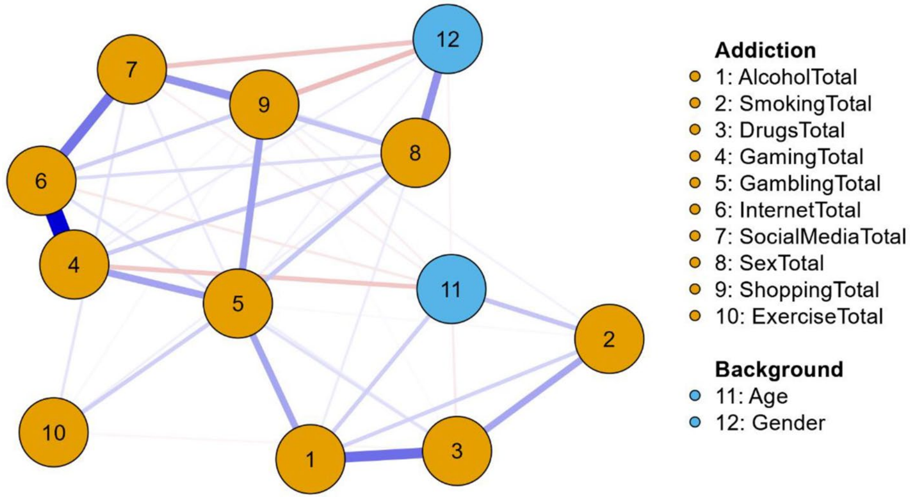

Fig. 1 Network of the addiction dimensions from the network analyses. *Note*. Blue lines represent positive associations and red lines negative associations. The thickness and brightness of an edge indicate the association strength. The layout is based on the Fruchterman–Reingold algorithm that places the nodes with stronger and/or more connections closer together and the more to the center and less strong and/or less connected nodes in the periphery

Table 3 Centrality indices of the addiction dimensions from the network analyses

Variable	Betweenness	Closeness	Strength	Expected influence
Alcohol	0.97	0.54	0.04	0.58
Cigarette smoking	−0.95	−1.26	−1.10	−0.26
Drugs	−0.13	−0.40	−0.27	0.01
Gaming	0.97	1.11	1.12	0.71
Online gambling	2.33	1.76	0.72	1.08
Internet	0.01	0.74	1.52	1.40
Social media	−0.13	0.35	0.68	0.16
Sex	−0.95	−0.21	0.25	0.74
Shopping	0.15	0.51	0.41	−0.14
Exercise	−0.95	−1.51	−1.99	−1.03
Age	−0.54	−0.73	−0.82	−1.73
Gender	−0.81	−0.91	−0.55	−1.53

Higher numbers indicate that the variable is more central to the network; the highest two values are underlined within each index

social media with sex and exercise, and sex with shopping and exercise. All these associations were positive. Also, there were positive associations for alcohol with social media, cigarette smoking with gambling, gaming with shopping, shopping with exercise, and negative association for drugs (undifferentiated) with exercise. Overall, there was one edge of large effect size and two edges of moderate effect sizes. Thus, only 6.66% (3/45) of nodes had effects that were considered important and worthy of interpretation. There were 5 and

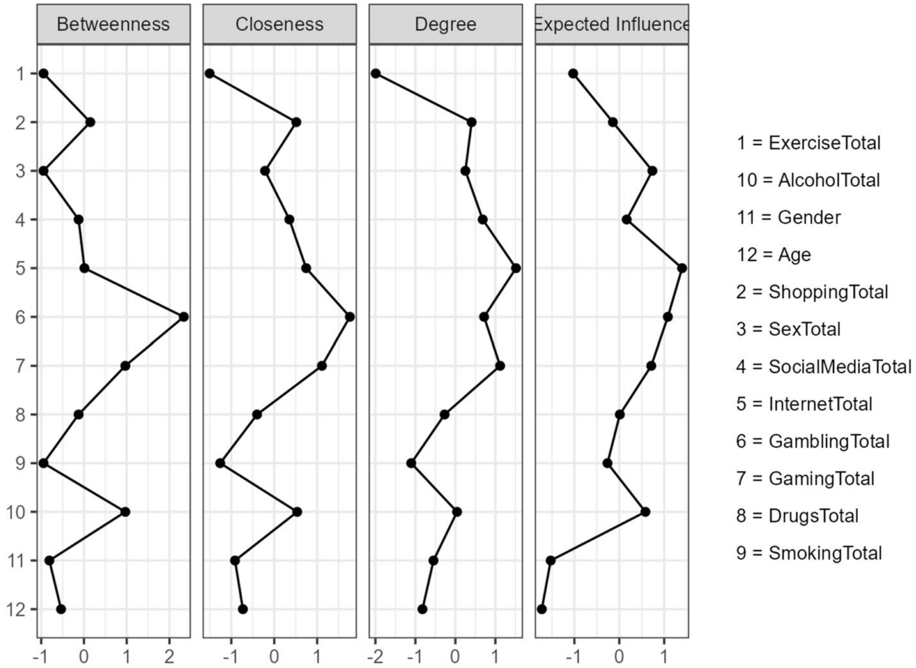

Fig. 2 Centrality plots (betweenness, closeness, degree, and expected influence) in the network of the addiction dimensions from the network analyses. Note. Values shown on the x-axis are standardized *z*-scores

Table 4 Weight matrix (partial correlations) for the addiction dimensions from the network analyses

	1	2	3	4	5	6	7	8	9	10	11	12
Alcohol (1)	.00	.09	.31	.00	.19	.00	.01	.04	.00	.00	.10	.00
Cigarette smoking (2)		.00	.19	.00	.01	.00	.00	.00	.03	.00	.12	.00
Drugs (3)			.00	.00	.03	.06	.00	.00	.00	−.02	−.04	.00
Gaming (4)				.00	.19	.54	.00	.11	.02	.00	−.12	.04
Online gambling (5)					.00	.00	.04	.12	.20	.10	.00	.03
Internet (6)						.00	.29	.07	.10	.00	−.05	.00
Social media (7)							.00	.12	.23	.05	−.03	−.13
Sex (8)								.00	.06	.03	.00	.23
Shopping (9)									.00	.01	−.03	−.14
Exercise (10)										.00	.00	.00
Age (11)											.00	−.03
Gender (12)												.00

For gender, men were coded as 1, and women were coded as 0

14 edges that had small and negligible effect sizes, respectively. Thus, when small effects are taken into consideration, there were 22 (1 + 2 + 5 + 14 = 22) edges that were significant or 48.88% (22/45).

Additionally, our findings indicated that age was associated positively with alcohol and cigarette smoking and negatively with drugs (undifferentiated), gaming, internet use, social media, and shopping. Gaming, gambling, and sex were associated more with being a man. Social media and shopping were associated more with being a woman. The other addictions were not differentially associated with age or gender.

Accuracy of Edge Weights and Stability of the Centrality Strength Index

The accuracy of the edges, estimated using bootstrap 95% non-parametric CIs, is shown in Supplementary Figure S1. As will be noticed, almost all of the 95% CI of the edges included zero, and the CIs around the estimated edge weights were relatively small. These findings can be interpreted as indicating the accuracy and stability of the edge findings.

The results of the case-dropping bootstrapping for examining the stability of the centrality indices are shown in Supplementary Figure S2. The figure shows that although there was a slight drop in the correlations as subset samples decreased from 95% of the original sample to 25% of the sample, this drop was never below 0.5 and was above 0.7. This indicates stability for the centrality indices (Epskamp et al., 2018).

Discussion

Summary of Major Network Findings

The study aimed to use network analysis to examine the network properties of a model comprising ten common substance-use and behavioral addictions (alcohol, cigarette smoking, drug, sex, social media, shopping, exercise, gambling, internet gaming, and internet use) co-occurring together (controlling for age and gender). We examined this for ratings of relevant addiction questionnaires completed by adults from the general community. In brief, our key findings were that (1) in the network graph, exercise, addictions categorized as behavioral addictions, and substance-use addictions were clustered in different sections; (2) internet use was the most central addiction, followed by gaming and then gambling; and cigarette smoking followed by exercise had the two lowest centrality values; and (3) there was large effect size association between gaming and internet use, and medium effect size associations for alcohol and drugs (undifferentiated), and internet use and social media. Additionally, there was support for the reliability (the stability and accuracy) of indices for centrality and edges, thereby indicating support for the interpretation of our findings.

Comparison of Findings in the Current Study to that Reported by Zarate et al. (2022)

As mentioned previously, for the same group of participants and addictions as in this study, Zarate et al. (2022) applied network analysis at the item level to examine the central addictions and/or the important associations between the different addictions. Their findings for centrality indicated that the highest centrality was gambling followed in sequence by internet use, internet gaming, alcohol, shopping, social media use, drugs (undifferentiated), sex, smoking, and exercise. Also, there were positive associations across different addictions. Overall, our findings differ from that reported by Zarate et al. (2022) in two important ways. Unlike our findings, the finding by Zarate et al. reported different addictions as central (gambling followed in sequence by internet use, internet gaming, and alcohol), and also, we were not able to demonstrate generally positive associations across different addictions. Zarate et al. (2022) concurred with our findings in that smoking followed by exercise had the two lowest centrality values. However, the difference noted here is related to the fact that while the present study used addictions as constructs in our network model, Zarate et al. (2022) used all the items from the different addictions. Overall, the present study, when considered in relation to Zarate et al. (2022) work, indicates that revising/amending the perspective of the network analysis applied (i.e., constructs instead of symptoms of addictive behaviors) can significantly expand the available knowledge.

Implications of Network Findings

First, from a network perspective, the nodes with high centrality suggest that they are important. Given that internet usage followed by gaming and then gambling had the top three centrality values, it follows that these addictions are especially important and central for understanding the co-occurrence of addictions (at least across the addictions included in the network in this study). In contrast, as cigarette smoking and exercise had the two lowest centrality values, these addictions can be considered having the least importance for understanding the co-occurrence of addictions (at least across the addictions included in the network in this study). Additionally, given that a network is considered a causal system, interacting with each other in meaningful ways (Borsboom & Cramer, 2013) and as the node with the highest centrality value is considered as being most influential, it follows from our findings that intervening on internet usage can be expected to spread to other addictions and maximize the impact of an intervention.

Second, traditionally, the influence of a variable is viewed in terms of its severity and interpreted in terms of its mean scores, with higher scores seen as more influential. In the current study, the addictions with the top three mean scores were, in order, internet usage, gaming, and exercise, and the addictions with the lowest two mean scores were drugs (undifferentiated) and alcohol. Thus, when the network centrality values and mean scores of the addictions are considered together, we have different conclusions about the relative influence of the different addictions examined in the study. Relatedly, our findings also support the notion that means scores are different from their network-based centrality values (Yang et al., 2016).

Third, our findings for edge weights can be seen as providing a better understanding of the interrelations between the ten addictions in the network model, particularly as the regularized partial correlation was computed, thereby showing only the more important associations between pairs of variables (Borsboom & Cramer, 2013; von Klipstein et al., 2021), controlling for all other variables in the model. Thus, compared to correlation analysis and multiple regression analysis, the findings in the network will be not confounded by shared variables involving other addictions. The edge weight findings in the study indicating a large effect size association between gaming and internet use would point to a strong association between these addictions. The findings for medium effect size association between alcohol and drugs (undifferentiated), and internet use and social media indicated moderate associations between these addictions. Also, the findings of small effect size associations for cigarette smoking and drugs (undifferentiated), alcohol and gambling, gaming and gambling, gambling and shopping, and social media and shopping indicated lower (but meaningful) associations between these addictions. Other associations were of negligible effect sizes. As small and negligible effect sizes were not considered important, they are not of major focus in the study. The edge weight findings can be interpreted in terms of comorbidity. If we consider the edge weights with high and medium as clinically meaningful, our edge weight findings can be interpreted as indicating that there is high comorbidity for gaming with internet use, alcohol with drugs (undifferentiated), and internet use with social media. Consistent with these findings, previous studies have also shown a robust and strong association between internet use with video game addiction (Gunuc, 2015) and social media addiction (Chen et al., 2022) and also alcohol and drugs (Karriker-Jaffe et al., 2018; Kendler et al., 2008; Verweij et al., 2018). Additionally, Kendler et al. (2008) have shown that nicotine, alcohol, and cannabis addictive behaviors presented with a similar emergence pattern, with family-related influences playing a significant role in early adolescence and declining/diminishing between 35 and 40 years, while genetic influences/predisposition effects became stronger over the life-course. Interestingly, Verweij et al. (2018) demonstrated using mendelian randomization that causal associations between different addictive behaviors (i.e., one causing the other) do not explain their co-occurrence-at least for nicotine, alcohol, caffeine, and cannabis use.

Fourth, given the findings and arguments that there is considerable overlap among the addictions and that they are likely to represent the different manifestations of the same underlying disorder (Kim & Hodgins, 2018; Marmet et al., 2018, 2019; Shaffer et al., 2004; Sussman et al., 2011; Sussman & Arnett, 2014), it was expected that most of the addictions will be correlated with each other and also be of reasonable magnitude. However, our network findings did not meet these expectations. It showed only 6.66% (3/45) of addictions had moderate or high effect sizes, and only 48.88% of the associations between the addictions were significant. In contrast to our network findings, in our previous study (involving the same group of participants and addiction), correlation analyses revealed that apart from the associations for cigarette smoking with gaming and social media, exercise with alcohol and substance use, and online gambling and internet, all other associations (40 in all or 88.88%) were significantly associated positively with each. Thus, compared to the correlation findings, fewer associations were found in the network analysis ($\chi^2 = 27.369$, $p < 0.001$). Given that the network findings are less confounded than the findings from the correlation analysis, our network findings could be considered being more credible. Considering this, our findings are not consistent with the view that the different addictions have considerable overlap and that they are different manifestations of the same underlying disorder. The opposite view which states that different addictions do not have considerable overlap and are not different manifestations of the same underlying disorder is more probable. We speculate that the relations between the different addictions are comparable to how anxiety and depression are related. Although anxiety and depression are closely related disorders, and they have some degree of shared etiological, phenomenological, clinical presentations, and even genetic vulnerabilities, anxiety and depression are considered different disorders (Anderson & Hope, 2008; Eysenck & Fajkowska, 2018).

Fifth, our finding indicates that exercise, other behavioral addictions (sex, social media, shopping, gambling, internet gaming, and internet use), and substance-use addictions (alcohol, cigarette smoking, and drugs (undifferentiated)) were clustered together in different sections, suggesting that the ten addictions in the model can be grouped into three groups: substance-use addictions, behavioral addictions not including exercise, and exercise by itself. This is consistent with the findings reported by Gomez et al. (2022) for the same group of participants and addictions as in the current study.

Sixth, although not a study aim, our findings indicated that being of older age was associated with alcohol and cigarette smoking and being of younger age was associated with drugs (undifferentiated), gaming, internet use, social media, and shopping. Gaming, gambling, and sex were associated more with men, whereas social media and shopping were associated more with women. Considering these findings, all future addiction research must be designed with sex and age being considered.

Seventh, the present study conducted a network study at the construct level; however, Zarate et al. (2022) conducted the network analysis for the same participants for the same set of addictions using the items in the questionnaires covering the addictions. As different findings were found across the two studies, we wish to note that findings would vary in terms of when the network analysis involves the symptoms or the dimensions for the symptoms. Relatedly, such different findings justify the goals of this study.

Given that this study is the first to use network analysis to examine co-occurring addictions at the construct level, our findings, and interpretations can be considered novel, with the potential to contribute further to our understanding of the co-occurrence of addictions. Despite this, there are limitations in the study, as discussed next, that must be kept in mind when considering the findings and interpretations made in the study.

Study Limitations

First, although we used network analysis with partial regularized correction, “true” causality cannot be assumed as the present study used cross-sectional data that utilized a convenience non-probabilistic sampling design. At best, we were able to eliminate spurious candidates for causal relations, and it is not possible to extrapolate the results. Secondly, as the network analysis was conducted using a normative-adult community sample, the findings cannot be directly generalized to other samples, such as clinical groups (including those with pathological levels of addiction problems and other psychopathologies), different age cohorts, or other groups of specific demographic characteristics (such as specific ethnic, cultural, and national groups). Thirdly, as the sample was obtained non-randomly, mainly comprised of males and contained a non-homogeneous distribution of age, this may have impacted the results and thus the generalization of the conclusions. Fourthly, psychiatric comorbidities and neurodevelopmental factors may significantly influence the clinical picture of addictions. As these were not considered in the current, there is a possibility that they could have confounded findings. Additionally, self-report measures were used, and the findings may be confounded with common method variance and may not be applicable to data collected via clinical interviews. Also, as our results are based on a single study, there is a need for more studies and replications before our findings can be generalized with confidence. Therefore, there is a need for more network studies on the co-occurrence of addictions. Lastly, the drug abuse measure employed inevitably restricts the extrapolation of the findings, as it may be too broad of a category (i.e., may not encounter for substance specific effects). Therefore, it is possible that the results may differ if provided in/specified different categories (e.g., antidepressants, stimulants, hallucinogens). For the same reason, our interpretation of our findings in the context of previous findings is also limited. Despite these limitations, our findings do offer new insights into the characteristics of the co-occurrence of addictions.

Conclusions

Overall, the current study is the first to use network analysis to explore the central addictions in a group of 10 common co-occurring addictions and to tease out the unique associations between them and in that way provide new and novel contributions to our understanding of the common addictions. The more novel and important findings are that only 6.66% of addictions have moderate or high effect sizes, and only 48.88% of the potential addictions were significant. These findings do not suggest considerable overlap among addictions, and that the different addictions are different manifestations of the same underlying disorder. Instead, based on our finding, it is suggested that while there is a possibility that some of the addictions (e.g., gaming and internet use, alcohol and drugs, and internet and social media use) are reasonably closely related; on the whole, the majority of the addictions (especially the behavioral addiction) are not closely associated and, therefore, may reflect different problems. Notwithstanding this, the study findings showed that the addiction with the highest centrality was internet use, followed by gaming and then gambling. Additionally, there was a relatively strong association between gaming and internet usage and relatively moderate associations between alcohol and drugs and internet and social media use. Thus, it can be argued that these addictions and the associations between them must be prioritized in theoretical and treatment models of co-occurring addictions. Although we have identified a number of study limitations, our findings do offer new insights into the co-occurrence of addictions and the need for more network analysis studies in this area, controlling for the limitations highlighted earlier.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11469-022-00995-8.

Author Contribution RG: Contributed to the literature review, the data collection framework formulation, data analysis, and the structure and sequence of theoretical arguments.

TB: Contributed to the literature review and reviewed the final form of the manuscript and final submission.

DT: Contribute to the literature review, data analysis, and reviewed the final form of the manuscript.

VS: Contributed to the data collection, literature review, structure, and sequence of theoretical arguments and reviewed the final form of the manuscript.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Data Availability The data that support the findings of this study are available from the corresponding author, TB, upon reasonable request.

Declarations

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.

Conflict of Interest The authors declare no competing interests.

Informed Consent Informed consent was obtained from all patients for being included in the study.

Confirmation Statement The authors confirm that this paper has not been either previously published or submitted simultaneously for publication elsewhere.

References

American Society of Addiction Medicine [ASAM]. (2019, May 14). *Definition of addiction.* ASMA. https://www.asam.org/quality-care/definition-of-addiction. Accessed 14 May 2022.

Anderson, E. R., & Hope, D. A. (2008). A review of the tripartite model for understanding the link between anxiety and depression in youth. *Clinical Psychology Review, 28*(2), 275–287. https://doi.org/10.1016/j.cpr.2007.05.004

Andreassen, C. S., Griffiths, M. D., Gjertsen, S. R., Krossbakken, E., Kvam, S., & Pallesen, S. (2013). The relationships between behavioral addictions and the five-factor model of personality. *Journal of Behavioral Addictions, 2*(2), 90–99. https://doi.org/10.1556/JBA.2.2013.003

Becker, J. B., & Chartoff, E. (2019). Sex differences in neural mechanisms mediating reward and addiction. *Neuropsychopharmacology, 44*(1), 166–183. https://doi.org/10.1038/s41386-018-0125-6

Becker, J. B., McClellan, M. L., & Reed, B. G. (2017). Sex differences, gender and addiction. *Journal of Neuroscience Research, 95*(1–2), 136–147. https://doi.org/10.1002/jnr.23963

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

Boschloo, L., van Borkulo, C. D., Rhemtulla, M., Keyes, K. M., Borsboom, D., & Schoevers, R. A. (2015). The network structure of symptoms of the diagnostic and statistical manual of mental disorders. *PLoS ONE, 10*(9), e0137621. https://doi.org/10.1371/journal.pone.0137621

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

Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review, 125*(4), 606–615. https://doi.org/10.1037/rev0000108

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., ... & Snippe, E. (2019). What do centrality measures measure in psychological networks?. *Journal of abnormal psychology*, *128*(8), 892-903.https://doi.org/10.1037/abn0000446

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*, 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*(4), 383–401. https://doi.org/10.1007/s40429-019-00279-7

Charzyńska, E., Sussman, S., & Atroszko, P. A. (2021). Profiles of potential behavioral addictions' severity and their associations with gender, personality, and well-being: A person-centered approach. *Addictive Behaviors, 119*, 106941. https://doi.org/10.1016/j.addbeh.2021.106941

Chen, B. C., Chen, M. Y., Wu, Y. F., & Wu, Y. T. (2022). The relationship of social media addiction with internet use and perceived health: The moderating effects of regular exercise intervention. *Frontiers in Public Health, 10*, e854532. https://doi.org/10.3389/fpubh.2022.854532

Christensen, A. P., & Golino, H. (2021). On the equivalency of factor and network loadings. *Behavior Research Methods, 53*(4), 1563–1580. https://doi.org/10.3758/s13428-020-01500-6

Cotto, J. H., Davis, E., Dowling, G. J., Elcano, J. C., Staton, A. B., & Weiss, S. R. (2010). Gender effects on drug use, abuse, and dependence: A special analysis of results from the National Survey on Drug Use and Health. *Gender Medicine, 7*(5), 402–413. https://doi.org/10.1016/j.genm.2010.09.004

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods, 23*, 617–634. https://doi.org/10.1037/met0000167

Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*, 1–18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). Generalized network psychometrics: Combining network and latent variable models. *Psychometrika, 82*(4), 904–927. https://doi.org/10.1007/s11336-017-9557-x

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*, 195–212. https://doi.org/10.3758/s13428-017-0862-1

Eysenck, M. W., & Fajkowska, M. (2018). Anxiety and depression: Toward overlapping and distinctive features. *Cognition and Emotion, 32*(7), 1391–1400. https://doi.org/10.1080/02699931.2017.1330255

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), e0227644. https://doi.org/10.1371/journal.pone.0227644

Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. *Advances in Neural Information Processing Systems*, *23*. https://doi.org/10.48550/arXiv.1011.6640

Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and experience, 21*(11), 1129–1164. https://doi.org/10.1002/spe.4380211102

Gomez, R., Stavropoulos, V., Brown, T., & Griffiths, M. D. (2022). Factor structure of ten psychoactive substance addictions and behavioural addictions. *Psychiatry Research, 313*, e114605. https://doi.org/10.1016/j.psychres.2022.114605

Grant, J. E., Potenza, M. N., Weinstein, A., & Gorelick, D. A. (2010). Introduction to behavioral addictions. *The American Journal of Drug and Alcohol Abuse, 36*(5), 233–241. https://doi.org/10.3109/00952990.2010.491884

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use, 10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Gunuc, S. (2015). Relationships and associations between video game and Internet addictions: Is tolerance a symptom seen in all conditions. *Computers in Human Behavior, 49*, 517–525. https://doi.org/10.1016/j.chb.2015.03.063

JASP Team (2020). JASP (Version 0.14.1) [Computer software].

Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M., ... & Billieux, J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours?. *Addiction*, *112*(10), 1709-1715.https://doi.org/10.1111/add.13763

Karriker-Jaffe, K. J., Li, L., & Greenfield, T. K. (2018). Estimating mental health impacts of alcohol's harms from other drinkers: Using propensity scoring methods with national cross-sectional data from the United States. *Addiction, 113*(10), 1826–1839. https://doi.org/10.1111/add.14283

Kendler, K. S., Schmitt, E., Aggen, S. H., & Prescott, C. A. (2008). Genetic and environmental influences on alcohol, caffeine, cannabis, and nicotine use from early adolescence to middle adulthood. *Archives of General Psychiatry, 65*(6), 674–682. https://doi.org/10.1001/archpsyc.65.6.674

Kim, H. S., & Hodgins, D. C. (2018). Component model of addiction treatment: A pragmatic transdiagnostic treatment model of behavioral and substance addictions. *Frontiers in Psychiatry, 9*(406), 1–17. https://doi.org/10.3389/fpsyt.2018.00406

KonkolÿThege, B., Hodgins, D. C., & Wild, T. C. (2016). Co-occurring substance-related and behavioral addiction problems: A person-centered, lay epidemiology approach. *Journal of Behavioral Addictions, 5*(4), 614–622. https://doi.org/10.1556/2006.5.2016.079

Kotyuk, E., Magi, A., Eisinger, A., Király, O., Vereczkei, A., Barta, C., ... & Demetrovics, Z. (2020). Co-occurrences of substance use and other potentially addictive behaviors: Epidemiological results from the Psychological and Genetic Factors of the Addictive Behaviors (PGA) Study. *Journal of Behavioral Addictions*, *9*(2), 272-288.https://doi.org/10.1556/2006.2020.00033

Leme, D. E. D. C., Alves, E. V. D. C., Lemos, V. D. C. O., & Fattori, A. (2020). Network analysis: A multivariate statistical approach for health science research. *Geriatrics, Gerontology and Aging, 14*(1), 43–51. https://doi.org/10.5327/Z2447-212320201900073

Marmet, S., Studer, J., Rougemont-Bücking, A., & Gmel, G. (2018). Latent profiles of family background, personality and mental health factors and their association with behavioural addictions and substance use disorders in young Swiss men. *European Psychiatry, 52*, 76–84. https://doi.org/10.1016/j.eurpsy.2018.04.003

Marmet, S., Studer, J., Wicki, M., Bertholet, N., Khazaal, Y., & Gmel, G. (2019). Unique versus shared associations between self-reported behavioral addictions and substance use disorders and mental health problems: A commonality analysis in a large sample of young Swiss men. *Journal of Behavioral Addictions, 8*(4), 664–677. https://doi.org/10.1556/2006.8.2019.70

Mullarkey, M. C., Marchetti, I., & Beevers, C. G. (2019). Using network analysis to identify central symptoms of adolescent depression. *Journal of Clinical Child & Adolescent Psychology, 48*(4), 656–668. https://doi.org/10.1080/15374416.2018.1437735

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks, 32*(3), 245–251. https://doi.org/10.1016/j.socnet.2010.03.006

Perales, J. C., King, D. L., Navas, J. F., Schimmenti, A., Sescousse, G., Starcevic, V., ... & Billieux, J. (2020). Learning to lose control: A process-based account of behavioral addiction. *Neuroscience & Biobehavioral Reviews*, *108*, 771-780.https://doi.org/10.1016/j.neubiorev.2019.12.025

Reer, F., Festl, R., & Quandt, T. (2021). Investigating problematic social media and game use in a nationally representative sample of adolescents and younger adults. *Behaviour & Information Technology, 40*(8), 776–789. https://doi.org/10.1080/0144929X.2020.1724333

Richter, L., Pugh, B. S., Smith, P. H., & Ball, S. A. (2017). The co-occurrence of nicotine and other substance use and addiction among youth and adults in the United States: Implications for research, practice, and policy. *The American Journal of Drug and Alcohol Abuse, 43*(2), 132–145. https://doi.org/10.1080/00952990.2016.1193511

Roberts, A., Rogers, J., Mason, R., Siriwardena, A. N., Hogue, T., Whitley, G. A., & Law, G. R. (2021). Alcohol and other substance use during the COVID-19 pandemic: A systematic review. *Drug and Alcohol Dependence, 229*, 109150. https://doi.org/10.1016/j.drugalcdep.2021.109150

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.https://doi.org/10.1007/s11469-021-00590-3

Santos, H. P., Jr., Kossakowski, J. J., Schwartz, T. A., Beeber, L., & Fried, E. I. (2018). Longitudinal network structure of depression symptoms and self-efficacy in low-income mothers. *PLoS ONE, 13*(1), e0191675. https://doi.org/10.1371/journal.pone.0191675

Schluter, M. G., Hodgins, D. C., Wolfe, J., & Wild, T. C. (2018). Can one simple questionnaire assess substance-related and behavioural addiction problems? Results of a proposed new screener for community epidemiology. *Addiction, 113*(8), 1528–1537. https://doi.org/10.1111/add.14166

Shaffer, H. J., LaPlante, D. A., LaBrie, R. A., Kidman, R. C., Donato, A. N., & Stanton, M. V. (2004). Toward a syndrome model of addiction: Multiple expressions, common etiology. *Harvard Review of Psychiatry, 12*(6), 367–374. https://doi.org/10.1080/10673220490905705

Sussman, S., & Arnett, J. J. (2014). Emerging adulthood: Developmental period facilitative of the addictions. *Evaluation & the Health Professions, 37*(2), 147–155. https://doi.org/10.1177/0163278714521812

Sussman, S., Lisha, N., & Griffiths, M. (2011). Prevalence of the addictions: A problem of the majority or the minority? *Evaluation & the Health Professions, 34*(1), 3–56. https://doi.org/10.1177/0163278710380124

Thege, B. K., Woodin, E. M., Hodgins, D. C., & Williams, R. J. (2015). Natural course of behavioral addictions: A 5-year longitudinal study. *BMC Psychiatry, 15*(1), 1–14. https://doi.org/10.1186/s12888-015-0383-3

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (methodological), 58*(1), 267–288.

Verweij, K. J., Treur, J. L., & Vink, J. M. (2018). Investigating causal associations between use of nicotine, alcohol, caffeine and cannabis: A two-sample bidirectional Mendelian randomization study. *Addiction, 113*(7), 1333–1338. https://doi.org/10.1111/add.14154

von Klipstein, L., Borsboom, D., & Arntz, A. (2021). The exploratory value of cross-sectional partial correlation networks: Predicting relationships between change trajectories in borderline personality disorder. *PLoS ONE, 16*(7), e0254496. https://doi.org/10.1371/journal.pone.0254496

Yang, Z., Algesheimer, R., & Tessone, C. J. (2016). A comparative analysis of community detection algorithms on artificial networks. *Scientific Reports, 6*(1), 1–18. https://doi.org/10.1038/srep30750

Zarate, D., Ball, M., Montag, C., Prokofieva, M., & Stavropoulos, V. (2022). Unravelling the web of addictions: A network analysis approach. *Addictive Behaviors Reports, 15*, e100406. https://doi.org/10.1016/j.abrep.2022.100406

Authors and Affiliations

Rapson Gomez[1] · Taylor Brown[2] · Deon Tullett-Prado[2] · Vasileios Stavropoulos[2,3]

Rapson Gomez
rapson.gomez@federation.edu.au

Deon Tullett-Prado
deon.tulletprado@live.vu.edu.au

Vasileios Stavropoulos
vasileios.stavropoulos@vu.edu.au

[1] Federation University, Ballarat, Australia

[2] Victoria University, Footscray, Australia

[3] National and Kapodistrian University of Athens, Athens, Greece