Technology, Mind, and Behavior • Behavioral Addiction to Technology

Online Behavioral Addictions: Longitudinal Network Analysis and Invariance Across Men and Women

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Published on: Jan 01, 2023

DOI: https://doi.org/10.1037/tmb0000105

ABSTRACT

Online activity has become increasingly prevalent worldwide, raising concerns about potential online behavioral addictions (e.g., problematic social media use, disordered online gambling, internet gaming disorder, and problematic internet use in general). The aim of this study was to conduct a longitudinal network analysis of symptoms associated with online behavioral addictions to examine their interrelations and potential differences across one's biologically assigned gender (i.e., male, female). An online community sample of 462 adult participants (28.5% women, 69.5% men) completed self-rating questionnaires across two time-points one year apart. Participants' responses were assessed with Least Absolute Shrinkage and Selection Operator regularized partial correlations (EBICglasso) and invariance methods. Gender differences were observed, with online gaming symptoms showing higher centrality in men and disordered social media use in women. Additionally, disordered gaming and internet use symptoms were highly influential, followed by online gambling, and social media use. Longitudinal differences were observed across genders, suggesting their different vulnerability to problematic behaviors associated with online activities. Additionally, *mood modification* associated with disordered internet use and *impairment* due to disordered gaming were highly influential in longitudinal measures, increasing the likelihood of developing coexisting or persistent symptoms of internet use disorders over time. Conclusions and implications are addressed considering the emerging literature.

Keywords: internet use disorders, longitudinal network analysis, measurement invariance, online behavioral addictions

Funding: Vasileios Stavropoulos received funding by The Victoria University, Early Career Researcher Fund ECR 2020, No. 68761601. The Australian Research Council, Discovery Early Career Researcher Award, 2021, No. DE210101107.

Disclosures: Vasileios Stavropoulos is an editorial board reviewer. The rest of 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 article.

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 article has not been either previously published or submitted simultaneously for publication elsewhere.

Authors Contributions: Daniel Zarate and Genevieve Dorman contributed to the article's conceptualization, data curation, formal analysis, methodology, project administration, and writing of the original draft. Vasileios Stavropoulos, Maria Prokofieva, and Romana Morda contributed to writing, reviewing, and editing the final draft.

Data Availability: Data, analytic methods, syntax, and study materials are available by accessing the following link https://github.com/Daniel28052/online_behavioral_addictions (Zarate, 2022)

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The technological advancement experienced in the last two decades has seen significant increases in internet use and engagement with online activities (Anderson et al., 2017). While online activity may not be problematic when used in moderation, scholarly interest has emerged considering the possibility of disordered online activity, including disordered gaming (Pontes & Griffiths, 2016), problematic online gambling (González-Cabrera et al., 2020), problematic social media use (PSMU; Andreassen et al., 2016), and disordered internet use (Stavropoulos et al., 2013). These problematic behaviors have been described as the excessive use of online platforms to the extent that it affects daily functioning (Griffiths, 2005).

Conceptualizing Online Problematic Behaviors

Disordered online gaming and disordered gambling have been included in the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders–5th edition* (*DSM-5*; APA, 2013), with related criteria grounded in empirical evidence. These criteria include (a) *preoccupation* with the activity; (b) *withdrawal* symptoms when the activity is taken away; (c) *tolerance*, resulting in increased engagement with the activity to achieve desired excitement; (d) *relapse*, due to unsuccessful attempts to control the activity; (e) *loss of interest* in previous hobbies/activities with the exception of the problematic behavior; (f) *interpersonal conflict* due to excessive engagement with the activity; (g) *deception* about the amount of time/resources spent on the activity; (h) engaging with the activity to *escape* or cope with negative mood states (*mood modification*); and (i) experiencing *negative consequences* such as losing significant relationships, jobs, or career opportunities due to excessive engagement with the activity (Pontes et al., 2019; Stavropoulos, Monger, et al., 2022). Although gambling presents idiosyncratic criteria (i.e., chasing loses, or relying on financial aid to continue gambling), scholars highlight the confirmatory approach associated with shared conceptual components of behavioral addictions (Griffiths, 2019; Stavropoulos, Monger, et al., 2022).

Interestingly, certain online problematic behaviors that are yet to be recognized as behavioral addictions in diagnostic and statistical manuals of mental disorders, such as PSMU and disordered internet use, representing conceptual inconsistencies in the field (Bányai et al., 2017). For example, previous studies have associated PSMU with the use of exclusive platforms, presenting conflicting definitions of such problematic behavior (e.g., Facebook dependence, Andreassen et al., 2012; Wolniczak et al., 2013; Twitter addiction, Saaid et al., 2014; social media addiction, Andreassen et al., 2016). Similarly, scholars employ terms such as internet-related disorders, referring indistinctly to PSMU or any other activity facilitated via online platforms (Bányai et al., 2017). Finally, the ongoing debate considering the possibility of over-pathologizing everyday activities may have hindered conceptual clarity in the field (Kardefelt-Winther et al., 2017). Nevertheless, the large body of evidence highlighting the negative consequences of disordered online activity suggests the need for further research (Anderson et al., 2017; Delfabbro & King, 2020; Kovacs et al., 2022; Rozgonjuk et al., 2023; Stavropoulos et al., 2013; Zarate, Ball, et al., 2022).

Comorbid Online Problematic Behaviors

As the development of online platforms progresses, so does the potential for coexisting behavioral addictions (BA) exacerbated by the ease of access to the internet now available with smartphones (Montag et al., 2021). Delfabbro & King, 2020 suggest that a “digital convergence” could increase the likelihood of experiencing coexisting internet use disorders (i.e., social media addiction, internet addiction, internet gaming disorder, and online gambling disorder). Similarly, the Model of Compensatory Internet Use (Kardefelt-Winther, 2014) proposes that adverse life concerns can motivate turning to online platforms to alleviate negative feelings. As involvement in an online activity evolves into BA, adverse life concerns manifest, propelling one further toward the addictive behavior(s) to compensate and distract themselves from the snowballing negative emotions (Griffiths, 2017).

Indeed, scholars identified comorbid presentations of disordered online activity (such as problematic video game use) and suicidal thoughts (Mérelle et al., 2017), depression (Xu et al., 2020), anxiety (Stavropoulos et al., 2017), as well as comorbid problematic behaviors in online environments (Rozgonjuk et al., 2023; Zarate, Ball, et al., 2022). Interestingly, most studies observed significant associations between comorbid problematic presentations and/or mental health issues using cross-sectional samples, whereas longitudinal studies dispute this idea. For example, Coyne et al. (2020) observed no relationship between screen time and mental health issues. Due to these conflicting results, further longitudinal research is needed to examine coexisting presentations of problematic behaviors and mental health issues.

Gender Differences

Previous literature has identified gender differences in an individual's propensity to develop certain types of addictive behaviors (Charzyńska et al., 2021; Chen et al., 2017; McHugh et al., 2018; Pelissier & Jones, 2005; Pontes et al., 2019; Tang & Koh, 2017). For example, while males are more vulnerable to developing substance, gaming, gambling, and online porn consumption-related addictions, females appear more likely to experience problematic behaviors associated with excessive use of social networking sites, shopping, and even studying (Charzyńska et al., 2021; McHugh et al., 2018; Pelissier & Jones, 2005; Pontes et al., 2019; Zarate, Fullwood, et al., 2022). Similarly, research has indicated that there may be gender differences in the age of onset of such problematic behaviors, especially for behavioral addictions (e.g., gambling), with females more likely to have a mid-to-later life onset and males commonly displaying earlier difficulties (APA, 2013).

Considering specific online problematic behaviors, evidence suggests that while smartphones, social networking sites, and gambling addictions are associated with anxiety and sleep disturbances in both males and females, depression presents a higher risk for females (Chen et al., 2017; Desai & Potenza, 2008). Interestingly, gender-specific differences have been found in addiction (dis)engagement motivations, with males being motivated externally (i.e., motivation comes from an outside source) and females more internally motivated (i.e., the way they feel/think). However, in social networking sites addiction, fear of missing out appears to be a gender-independent motive, Li et al., 2022). Nevertheless, the applicability of such gender-related differences across different problematic behaviors is contested, and further research is needed in this area (Pontes et al., 2019). Therefore, the present study aims to contribute to the available literature by adopting a data-driven, network analysis (NA) approach to explore gender differences across technology-proposed related problematic behaviors.

Network Analysis

Despite the recent emergence of online BA, many studies have investigated different aspects of this problem (Kovacs et al., 2022; Stavropoulos, Dumble, et al., 2022; Stavropoulos, Footitt, et al., 2022). However, researchers often assess coexisting presentations of BA at the *disorder level*, overlooking the relationships between *symptoms of problematic behaviors*. Indeed, assessing problematic symptoms at the disorder level represents the current dominant perspective in psychopathology, and it assumes that a group of symptoms can be explained or reflected by a latent construct (van Borkulo et al., 2015). For example, the existence of disordered social media use (as a construct) explains or justifies symptoms associated with this disorder. However, this perspective detracts importance from the possibility of interpreting symptoms as activators of coexisting problematic presentations (van Rooij et al., 2017). Alternatively, novel approaches, such as NA, enable the interpretation of psychopathology symptoms as causative agents of specific disorders and the identification of influential symptoms that may activate or increase the likelihood of developing further problems (Haylett et al., 2004). For example, well-connected and central symptoms can be interpreted as "super spreaders", increasing the likelihood of symptom propagation. Finally, NA can be particularly effective in detecting variations of symptoms over time due to its ability to examine the level of influence a symptom may play in a given structure at different time-points (Epskamp et al., 2018).

The Present Study

Most research has investigated comorbid presentations of online behavioral addictions at the construct or disorder level, with only two studies assessing relationships between symptoms of problematic behaviors (Rozgonjuk et al., 2023; Zarate, Ball, et al., 2022). This study is the first to use a longitudinal design to explore the relationships between coexisting problematic behaviors in online environments (including internet use, internet gaming, online gambling, and social media use) at the symptom level and to explore potential gender differences in these relationships. This is important because it adds empirical evidence to identify potential activators of problematic online behaviors. This information can help clinicians identify specific problematic presentations for men and women and thus devise targeted interventions identifying symptoms that may increase the likelihood of activating different problematic behaviors (e.g., *mood modification* due to gaming may increase the likelihood of developing online gambling-related issues).

Therefore, this study aims to (a) examine the network structure and centrality of symptoms of problematic behavior in online environments (b) and its variations over time, and to (c) investigate potential differences across men and women. Accordingly, to address these aims, the following research questions have been proposed:*Research Question (RQ1):* What is the network structure and centrality indices of symptoms of problematic behavior in online environments (i.e., social media use, internet use, online gaming, online gambling)? *Research Question (RQ2):* Which problematic behaviors are more likely to increase the likelihood of developing further problematic behaviors? *Research Question (RQ3):* What differences are there according to gender in online problematic behaviors?

Method

Participants

The sample included 462 English-speaking adults from the USA, U.K., Australia, and New Zealand. Participants' age ranged from 18 to 62 years (M_{age} = 30.8, SD = 9.23) and included 132 females (28.5%, M_{age} = 30.3, SD = 9.71), 321 males (69.5%, M_{age} = 31.2, SD = 9.09), and 9 nonbinary (2%, M_{age} = 25.9, SD = 4.96). No significant differences in age across gender groups were observed, $F(2,459) = 1.76$, $p = .17$. Most participants were White/Caucasian (66.7%), heterosexual/straight (77.9%), and about half (48.3%) were in a romantic relationship. The powerly package for R Studio (Constantin et al., 2021) determined that a sample of 425 participants was needed to achieve acceptable statistical power ($1 - \beta = 0.8$, sensitivity = 0.6) for a Gaussian graphical network with 70 nodes (see Supplemental Figure 1).

Missing responses represented 6.45% and were completely at random (MCAR). Thus multiple imputations with predictive mean matching and 50 iterations using the MICE package for RStudio were conducted (Van

Buuren & Groothuis-Oudshoorn, 2011). No significant differences in most scores of problematic behaviors across gender groups were observed. However, women scored significantly higher than men in BSMAS time point 1, $F(2,459) = 4.46$, $p = .01$, and men higher than women in OGD-Q time point 1, *Welch's* $F(2,22.8) = 5.01$, $p = .02$. Pearson bivariate correlations observed significant relationships between all disorders including participants' age. Supplemental Table 1 presents participant sociodemographic information and problematic behavior information. Supplemental Table 2 presents a correlation matrix including problematic behavior symptoms and participants' age.

Measures

The *Internet Disorder Scale—Short Form—IDS9-SF* (Pontes & Griffiths, 2016) assessed internet addiction with nine items rated on a 5-point Likert scale ranging from 1 (*never*) to 5 (*very often*). Total scores range from 9 to 45, with higher scores indicating higher symptom severity. Examples of items include "Do you feel preoccupied with your online behavior?"

The *Online Gambling Disorder Questionnaire—OGD-Q* (González-Cabrera et al., 2020) assessed dysfunctional online gambling with eleven items rated on a 5-point Likert scale ranging from 1 (*never*) to 5 (*every day*). Total scores range from 11 to 55, with higher scores indicating higher symptom severity. Examples of items include "Do you feel nervous, irritated, or angry when trying to reduce or stop gambling?"

The *Bergen Social Media Addiction Scale—Short Form—BSMAS* (Andreassen et al., 2016) assessed disordered social media use with six items rated on a 5-point Likert scale ranging from 1 (*very rarely*) to 5 (*very often*). Total range from 6 to 30, with higher scores indicating higher symptom severity. Examples of items include "During the last year, I felt an urge to use social media more and more."

The *Internet Gaming Disorder Scale—Short Form—IGD9-SF* (Pontes & Griffiths, 2015) assessed disordered gaming symptoms with nine items rated on a 5-point Likert scale ranging from 1 (*never*) to 5 (*very often*). Total scores range from 9 to 45, with higher scores indicating higher symptom severity. Examples of items include "Do you feel preoccupied with your gaming behavior?" All instruments showed excellent internal consistency with Cronbach's α ranging from 0.89 to 0.94 and McDonald's ω from 0.87 to 0.90. Additionally, following the component model of addiction, Supplemental Table 3 identifies different addiction domains with their corresponding items in each disorder (e.g., IGD Item 1—*Salience*).

Procedure

The study was advertised via email (Victoria University student platform) and social media (*Facebook, Instagram, Reddit, Twitter*) after obtaining approval from the researchers' university Ethics committee. Individuals over 18 years were invited to complete two online surveys 1 year apart (the first wave between November 2020 and January 2021 and the second wave between November 2021 and January 2022). The online questionnaire included demographic questions and the four measures (i.e., IDS9-SF, OGD-Q, BSMAS, and IGD9-SF). A Plain Language Information Statement was available upon accessing the link to ensure participant eligibility criteria were met (i.e., being adults), obtain informed consent, and ensure participation was voluntary.

Statistical Analysis

This study conducted a NA to observe the relationships between symptoms of online problematic behaviors and included an assessment of the network's accuracy and stability (Epskamp et al., 2018). The Bootnet package for RStudio was used to estimate a network of regularized partial correlations between different symptoms of problematic online behaviors (Epskamp et al., 2018). Specifically, the Bootnet package employs the extended Bayesian information criterion (EBIC-LASSO) and a tuning hyperparameter (γ) to apply optimal regularization of partial correlations and thus eliminate spurious edges. This method has been recommended to increase the interpretability of polychoric correlations using polytomous data (i.e., obtained through Likert-type scales; Fried, 2017).

Subsequently, 1,000 nonparametric bootstrapped resampling were used to assess the network's accuracy (Epskamp et al., 2018). This approach allows the estimation of confidence intervals between the sample and bootstrapped mean values, with smaller errors representing higher accuracy of results. Additionally, stability of centrality indices was assessed using the case-dropping subset bootstrapping (Epskamp et al., 2018). This method uses correlation stability coefficients (CS) to assess if centrality indices remain stable when dropping incremental percentages of cases (5%, 10%, etc.), with CS > .5 as evidence of sufficient stability.

Upon estimation of the Least Absolute Shrinkage and Selection Operator-regularized network, an assessment of centrality indices and bridge symptoms was conducted. Centrality indices assess the importance/influence a specific symptom has on the overall network and include *strength, betweenness, closeness, and expected influence* (Hevey, 2018). *Strength* represents how many edges (or connections) a specific node (or symptom) has, with higher strength indicating higher centrality. *Betweenness* and *Closeness* provide measures of average distance between nodes, and *expected influence* represents the sum of edge weights accounting for both positive and negative relationships. Moreover, the analysis of *Bridge symptom centrality* involves examining centrality indices excluding intra-disorder node relationships to focus exclusively on inter-disorder node relationships (Vanzhula et al., 2021).

Finally, the network comparison test (NCT) package for RStudio was used to conduct invariance tests and thus compare network structures across men and women (van Borkulo et al., 2015). Specifically, to assess *network structure invariance*, the NCT uses random permutation testing to compare the largest absolute difference (M) between a pair of matrices (G_1 and G_2) and the distribution of permuted M, with $p < .05$ as evidence of noninvariance. Additionally, to assess *global strength invariance*, the NCT uses random permutation testing to compare the difference (S) of the absolute sum of all edges between a pair of matrices (G_1 and G_2) and the distribution of permuted S, with $p < .05$ as evidence of noninvariance.

Results

Network Accuracy and Stability

To assess the network's edge-weight accuracy, edge comparison between sample estimation and the bootstrapped mean (using 1,000 nonparametric bootstrapped resampling) was conducted (Epskamp et al., 2018). As seen in Supplemental Figure 2 (left panel), there were no large discrepancies between the sample values and the bootstrapped mean. However, some bootstrapped confidence intervals (95% CIs) exhibited larger standard errors indicating that the interpretation of results should be approached with caution. Additionally, the case-dropping subset bootstrapping was used to assess the stability of centrality indices (Epskamp et al., 2018). Expected influence ($CS_{[cor = 0.7]}$ = 0.59), strength ($CS_{[cor = 0.7]}$ = 0.59), and closeness ($CS_{[cor = 0.7]}$ = 0.52) showed acceptable proportions of case-dropping to retain correlations of 0.7 in at least 95% of the samples. However, betweenness ($CS_{[cor = 0.7]}$ = 0.05) fell below the recommended threshold (CS > 0.5) and was subsequently not emphasized in the present study (see Supplemental Figure 2, right panel).

Network of Problematic Behaviors

To answer *RQ1* and assess the relationships between symptoms of problematic online behaviors, a regularized network of partial correlations was estimated. This included 70 symptoms of four problematic behaviors in online environments, including social media use, online gambling, internet gaming and internet use (Figure 1). Of 2,415 possible edge weights, 432 were nonzero (17.9% sparsity), with a mean weight of 0.013. The strongest relationship between first-wave symptoms was OGD Item-10 *Borrowing due to gambling* and OGD Item-11 *Salience* ($\hat{r}$ = .04), and the strongest relationship between second-wave symptoms was IGD Item-9 *Impairment* and IDS Item-9 *Impairment* ($\hat{r}$ = .43). Finally, the strongest relationship between first and second-wave symptoms was IGD Item-8 (Wave 1) *Mood modification* and IGD Item-8 (Wave 2) *Mood modification* ($\hat{r}$ = .15). See Supplemental File 1 for the full regularized correlation matrix.

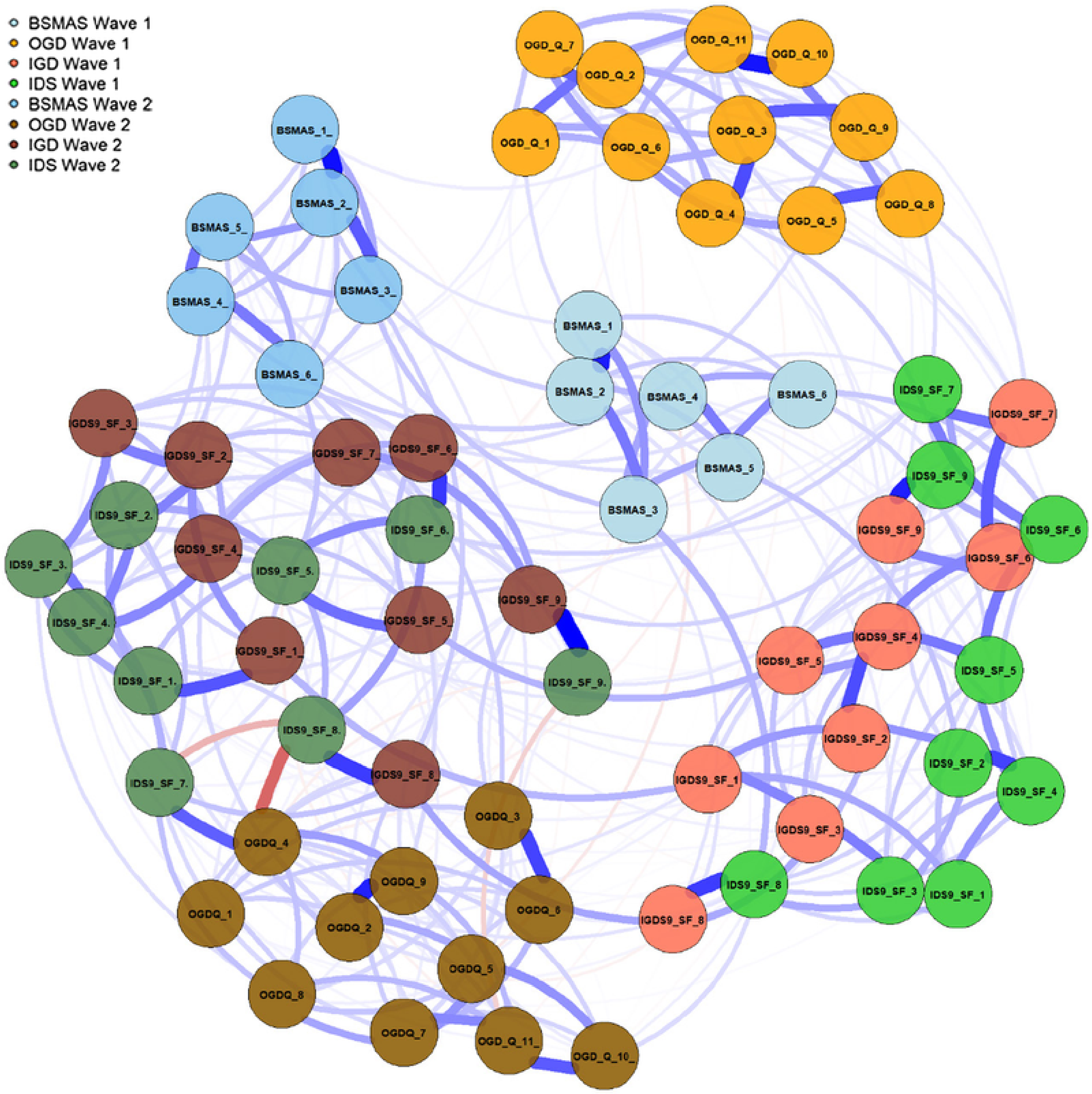

Figure 1
Visualization of the Regularized Network of Online BA Symptoms

Note. The 70 nodes represent symptoms of four online BA at two time-points (35 nodes first wave, and 35 s wave), with different color nodes assigned to different disorders. Regularized correlations are represented by edges (or lines), with thicker edges illustrating stronger relationships. Blue lines depict positive correlations, and red lines represent negative correlations. BA = behavioral addictions; BSMAS = Bergen Social Media Addiction Scale; IDS9-SF = Internet Disorder Scale—Short Form; OGD-Q = Online Gambling Disorder Questionnaire; IGDS9-SF = Internet Gaming Disorder Scale—Short Form.

Centrality Indices and Bridge Symptom Centrality

To evaluate the importance of specific symptoms, centrality indices were assessed, including strength, expected influence, closeness, and betweenness (Figure 2 left panel). Specifically, OGD Item-4 (Wave 2) *Interpersonal conflict* showed +2.40SD strength centrality, and IDS Item-8 (Wave 2) *Mood modification* showed +2.22SD strength centrality. Moreover, BSMAS item-2 (Wave 2) *Tolerance* showed +1.81SD expected influence, and IGDS Item-4 (Wave 1) *Relapse* showed +1.69SD expected influence. Finally, IDS Item-6 (Wave 2) *Psychosocial Problems* showed +2.09SD in closeness centrality, and IDS Item-8 (Wave 2) *Mood modification* showed +2.02SD. Supplemental Table 4 presents the ten most influential symptoms arranged by centrality index.

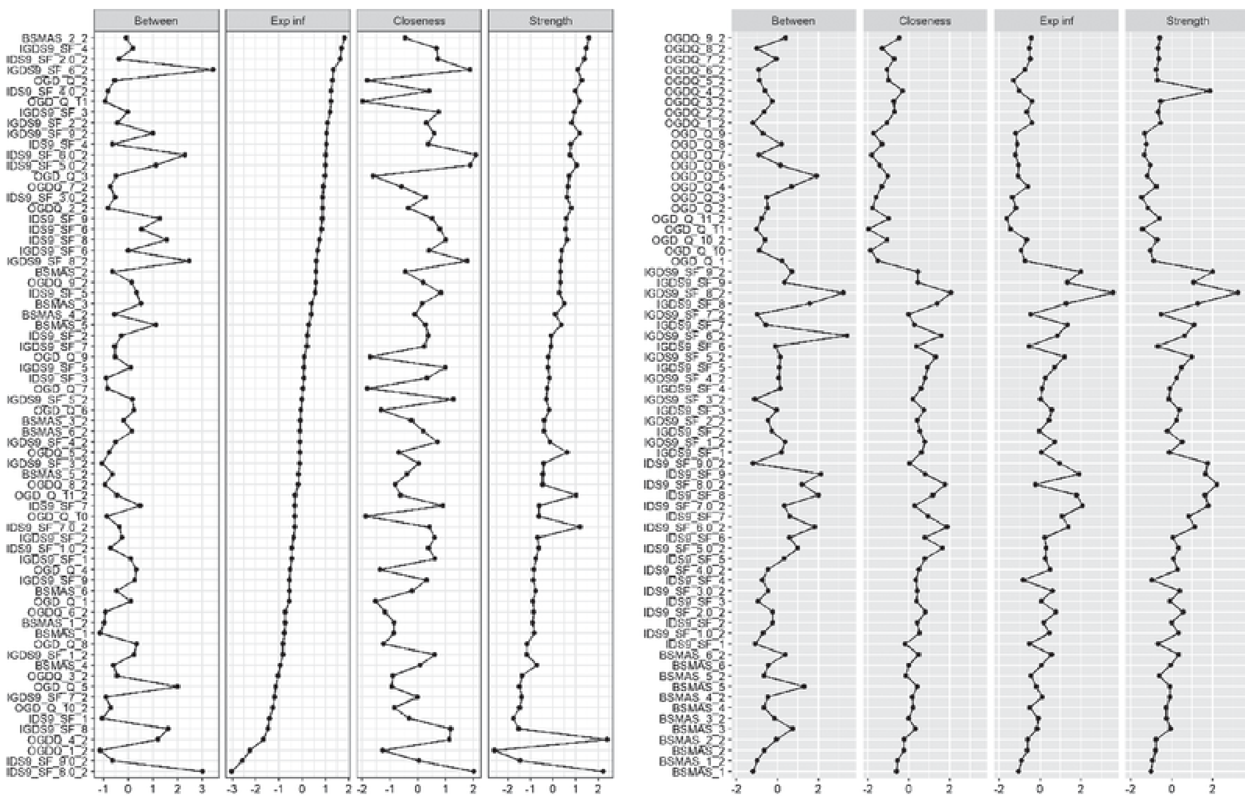

Figure 2
Centrality Indices and Bridge Symptoms

Note. The left panel shows standardized centrality indices on the horizontal axis and the symptoms of addiction on the vertical axis. Higher standardized scores represent increased symptom centrality. The right panel shows standardized bridge symptom centrality. BSMAS = Bergen Social Media Addiction Scale; IDS9-SF = Internet Disorder Scale—Short Form; OGD-Q = Online Gambling Disorder Questionnaire; IGDS9-SF = Internet Gaming Disorder Scale—Short Form.

Moreover, an assessment of bridge symptoms centrality was conducted to observe the influence of specific symptoms on other forms of problematic online behaviors (i.e., inter-disorder relationships; Vanzhula et al., 2021). Figure 2 (right panel) presents bridge symptom centrality indices for all symptoms of online BAs. Considering strength, IGD Item-8 (Wave 2) *Mood modification* showed +3.23SD, and IDS Item-8 (Wave 2) *Mood modification* showed +2.23SD. Considering expected influence, IGD Item-8 (Wave 2) *Mood modification* showed +3.57SD, and IDS Item-7 (Wave 2) *Deception* showed +2.06SD. Finally, considering closeness, IGD Item-8 (Wave 2) *Mood modification* showed +2.06SD, and IDS Item-6 (Wave 2) *Psychosocial Problems* showed +1.86SD. Supplemental Table 5 presents the ten most influential bridge symptoms arranged by centrality index.

Longitudinal Relationships

To answer RQ2 and assess which type of problematic online behavior is more likely to develop into further problematic behaviors, a focus on longitudinal relationships was emphasized, considering the effect of symptoms assessed during the first wave of data collection on symptoms assessed during the second wave of data collection. Accordingly, the most influential problematic behaviors at time point 1 were IGD Item-5 *Loss of interest* ($\hat{r}$ = .16), IGD Item-9 *Impairment* ($\hat{r}$ = .14), and IDS Item-7 *Deception* ($\hat{r}$ = .14; see most influential symptoms in Table 1). Interestingly, when excluding intra-disorder relationships, the most influential items were IDS Item-8 *Mood modification* ($\hat{r}$ = .11), IGD Item-9 *Impairment* ($\hat{r}$ = .07), and OGD Item-5 *Salience* ($\hat{r}$ = .06; see most influential bridge symptoms in Table 1). In other words, these items exerted the most influence on other disorders, increasing the likelihood of activating further problematic behaviors.

Table 1

Longitudinal Relationships Between Symptoms of Online Behavioral Addictions

Overall network				Males network				Females network			
Most influential symptoms	$\hat{r}$	Most influential bridge symptoms	$\hat{r}$	Most influential symptoms	$\hat{r}$	Most influential bridge symptoms	$\hat{r}$	Most influential symptoms	$\hat{r}$	Most influential bridge symptoms	$\hat{r}$
IGD 5	.16	IDS 8	.11	IGD 5	.19	IDS 8	.13	BSMAS 2	.16	OGD 5	.13
IGD 9	.14	IGD 9	.07	IGD 8	.18	IGD 3	.08	BSMAS 5	.16	IGD 1	.12
IDS 7	.14	OGD 5	.06	IDS 7	.17	IGD 5	.08	IGD 1	.14	IDS 8	.10

IGD 8	.13	IGD 3	.05	IGD 1	.16	OGD 5	.05	BSMAS 3	.13	IGD 9	.10
IGD 1	.13	IDS 9	.04	IGD 8	.15	IDS 7	.04	IGD 3	.13	OGD 1	.07
IDS 8	.19	OGD 1	.03	IGD 9	.13	IGD 9	.04	OGD 5	.13	BSMAS 5	.07
BSMAS 2	.08	IGD 5	.03	IGD 3	.11	OGD 1	.04	BSMAS 6	.12	IDS 2	.07
IGD 3	.07	OGD 2	.02	BSMAS 4	.09	IDS 9	.04	IGD 9	.11	IDS 9	.07
BSMAS 3	.07	IDS 2	.02	OGD 5	.07	IDS 5	.03	IGD 5	.11	OGD 2	.07
IGD 7	.06	IGD 2	.02	IGD 4	.07	IGD 1	.03	IGD 6	.10	OGD 7	.04

Note. Here are the most influential symptoms at Wave 1 on symptoms at Wave 1. These are arranged by the sum of interitem relationships ($\hat{r}$) , and the most influential bridge systems were obtained by excluding intra-system relationships (e.g., excluding the relationship between IGD 1 and IGD 2). IDS = Internet Disorder Scaleq BSMAS = Bergen Social Media Addiction Scale; OGD = online gambling disorder; IGD = Internet Gambling Disorder Scale.

At the disorder level, IGD was the most influential ($\hat{r}$ = .82) followed by IDS ($\hat{r}$ = .34), BSMAS ($\hat{r}$ = .33) and OGD ($\hat{r}$ = .11; see Supplemental File 2). Moreover, Table 2 shows the level of influence each disorder exerted on a different disorder. Specifically, BSMAS items at Wave 2 were mostly influenced by BSMAS items at Wave 1 ($\hat{r}$ = .41); OGD items at Wave 2 were mostly influenced by IDS items at Wave 1 ($\hat{r}$ = .19); IGD items at Wave 2 were mostly influenced by IGD items at Wave 1 ($\hat{r}$ = .64); and finally IDS items at Wave 2 were mostly influenced by IDS items at Wave 1 ($\hat{r}$ = .13). See Supplemental File 2 for a regularized correlation matrix focusing exclusively on longitudinal relationships.

Table 2

Longitudinal Relationships Between Symptoms of Online Behavioral Addictions

Disorder	Overall network				Males network				Females network			
	BSMAS	OGD	IDG	IDS	BSMAS	OGD	IDG	IDS	BSMAS	OGD	IDG	IDS
BSMAS	.41	-0.07	-.01	.01	.34	-.13	.03	.04	.54	.00	.02	.08

OGD	.06	-0.02	.08	.00	.05	.04	.06	-.01	.10	-.08	.21	.08
IDG	.00	.06	.64	.11	.02	.13	.67	.12	.00	.08	.53	.22
IDS	.00	.18	.03	.13	.01	.17	.17	.18	.05	.13	.15	.10

Note. This table presents longitudinal relationships to identify the level of influence a disorder has on another disorder. The rows represent disorders at the first wave, and the columns represent disorders at the second wave, with coefficients ($\hat{r}$) representing the sum of relationships between all items of a disorder at first wave and a disorder at second wave. For example, for the overall network (i.e., including men and women), the second-wave BSMAS was highly influenced by the first-wave BSMAS, whereas the second-wave OGD was highly influenced by the first-wave IDS. IDS = Internet Disorder Scale; BSMAS = Bergen Social Media Addiction Scale; OGD = online gambling disorder; IGD = Internet Gaming Disorder Scale.

Gender Differences in Online Problematic Behaviors

To answer RQ3, differences between symptoms of problematic online behaviors in men and women were explored. NCTs determined that male and female networks showed an invariant network structure ($M_{[453]}$ = 0.40, p = .23) and invariant global strength ($S_{[453]}$ = 2.28, p = 0.24; see Supplemental Figure 3). Moreover, networks of problematic online behaviors across gender groups showed similar sparsity (men: 441 nonzero edges [18.3%], mean weight = 0.014; women: 361 nonzero edges [14.9%], mean weight = 0.013; Figure 3).

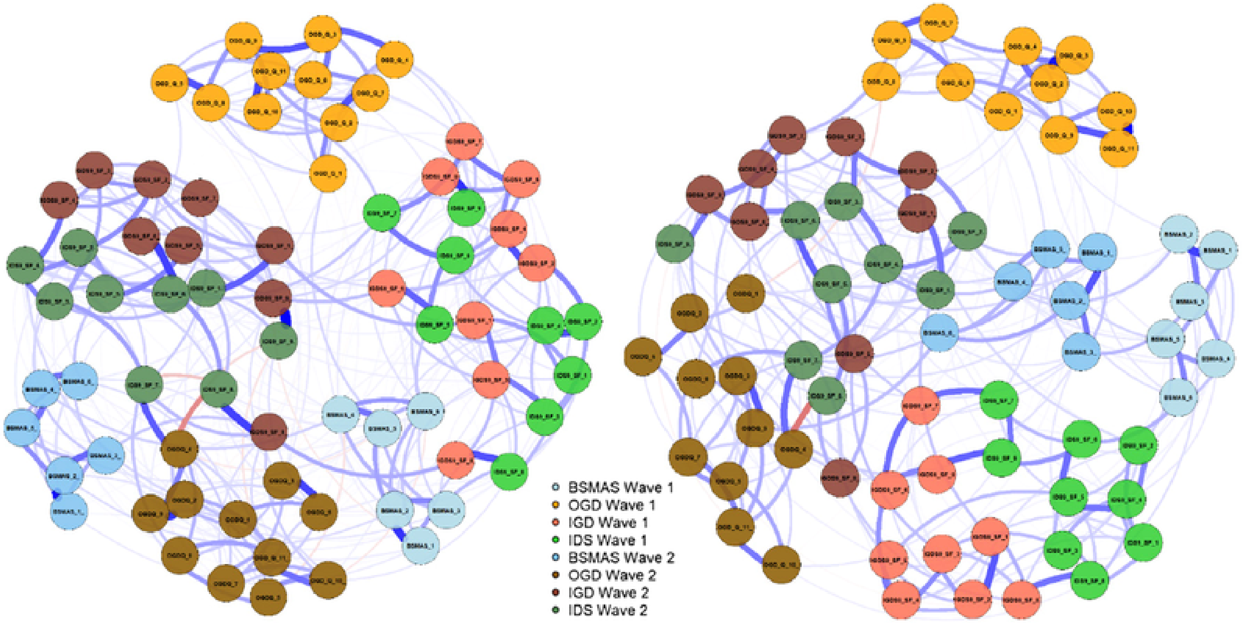

Figure 3
Visualization of the Regularized Network of Online BA Symptoms for Men (Left Panel) and Women (Right Panel)

Note. BA = behavioral addictions; BSMAS = Bergen Social Media Addiction Scale; IDS9-SF = Internet Disorder Scale—Short Form; OGD-Q = Online Gambling Disorder Questionnaire; IGDS9-SF = Internet Gaming Disorder Scale—Short Form.

Assessment of centrality indices showed differences between men and women (Figure 4 left panel). Considering strength centrality, OGD Item-4 (Wave 2) *Interpersonal conflict* (+2.69 *SD*) and IDS Item-4 (Wave 1) *Relapse* (+1.78 *SD*) showed a higher number of connections in men, whereas IDS Item-5 (Wave 2) *Loss of interest* (+1.83 *SD*) and IDS Item-4 (Wave 2) *Relapse* (+1.63 *SD*) showed higher number of connections in women. Considering expected influence, IGD Item-4 (Wave 1) *Relapse* (+1.97 *SD*) and IDS Item-6 (Wave 2) *Psychosocial problems* (+1.96 *SD*) showed a higher influence in men. In contrast, IDS Item-5 (Wave 2) *Loss of interest* (+1.67 *SD*) and IDS Item-4 (Wave 2) *Relapse* (+1.50 *SD*) showed a higher influence in women. See Supplemental Tables 6 and 7 for the ten most influential symptoms arranged by centrality index and discriminated by men and women.

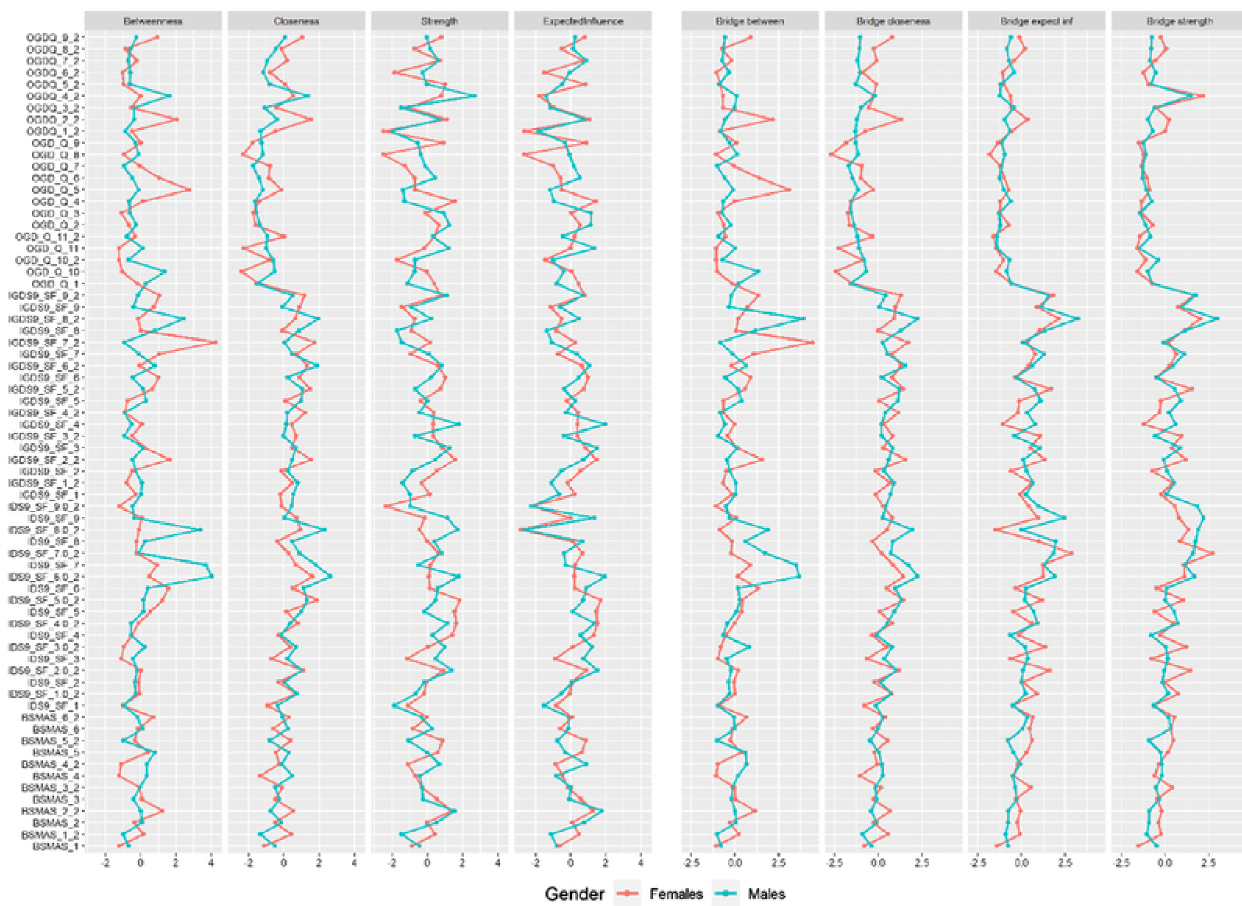

Figure 4

Centrality Indices and Bridge Symptoms Discriminated by Gender Groups

Note. The left panel shows standardized centrality indices on the horizontal axis and the symptoms of addiction on the vertical axis. Higher standardized scores represent increased symptom centrality. The right panel shows standardized bridge symptom centrality. The red lines indicate indices calculated for female participants, and the blue lines for male participants. BSMAS = Bergen Social Media Addiction Scale; IDS9-SF = Internet Disorder Scale—Short Form; OGD-Q = Online Gambling Disorder Questionnaire; IGDS9-SF = Internet Gaming Disorder Scale—Short Form.

Moreover, assessment of bridge symptom centrality showed differences between men and women (Figure 4 right panel). Considering strength, IGD 8 (Wave 2) *Mood modification* (+2.99 *SD*) and IDS 9 *Impairment* (+2.21 *SD*) showed a higher number of inter-disorder connections in men, whereas IDS 7 (Wave 2) *Deception* (+2.71 *SD*) and ODG 4 (Wave 2) *Interpersonal conflict* (+2.19 *SD*) showed a higher number of inter-disorder connections in women. Considering expected influence, IGD 8 (Wave 2) *Mood modification* (+3.23 *SD*) and IDS 9 *Impairment* (+2.43 *SD*) showed a higher influence in men, whereas IDS 7 (Wave 2) *Deception* (+2.84 *SD*) and IGD 8 (Wave 2) *Mood modification* (+2.15 *SD*) showed a higher influence in women. See Supplemental Tables 8 and 9 for the ten most influential bridge symptoms arranged by centrality index and discriminated by males and females.

Finally, the most influential problematic behaviors in men were IGD Item-5 *Loss of interest* ($\hat{r}$ = .19), IGD Item-8 *I* ($\hat{r}$ = .18), and IDS Item-7 *Deception* ($\hat{r}$ = .17), whereas the most influential problematic behaviors in women at time point 1 were BSMAS Item-2 *Tolerance* ($\hat{r}$ = .16), BSMAS Item-5 *Withdrawal* ($\hat{r}$ = .16) and IGD Item-1 *Salience* ($\hat{r}$ = .14; see Table 1). When excluding intra-disorder relationships, the most influential problematic behaviors in men were IDS Item-8 *Mood modification* ($\hat{r}$ = .16), IGD Item-3 *Tolerance* ($\hat{r}$ = .08), and IGD Item-5 *Loss of interest* ($\hat{r}$ = .08). Alternatively, the most influential problematic behaviors in women were OGD Item-5 *Salience* ($\hat{r}$ = .13), IGD Item-1 *Salience* ($\hat{r}$ = .12) and IDS Item-8 *Mood modification* ($\hat{r}$ = .10). Considering problematic behaviors at the disorder level, minimal differences between men and women were observed (Table 2).

Discussion

This study sought to expand the available knowledge of coexisting symptoms of disordered online activity, its variations over time, and the assessment of potential gender differences. To address these aims, a NA approach was implemented using an adult community sample to examine the relationship between symptoms of disordered online activity and the level of influence exerted by specific symptoms, resulting in the increased likelihood of developing new problematic behaviors. Self-rated questionnaires across two time-points 1 year apart assessed behaviors related to disordered online gaming, problematic online gambling, problematic social media use, and disordered internet use. The observed network structures showed acceptable accuracy and stability of relationships between symptoms.

Overall, symptoms of problematic behaviors formed cohesive networks with relative sparsity and strong intra-disorder relationships. This indicates that while problematic behaviors of a specific disorder may be related to other types of problematic behaviors, each disorder assessed here exhibits uniquely different presentations and should be addressed as such. Additionally, evidence of relationships between problematic behaviors shows that symptoms related to disordered gaming and disordered internet use were the most influential problematic behaviors increasing the likelihood of developing further problems or transitioning to new addictive behaviors. Interestingly, disordered social media symptoms showed greater influence in women, providing evidence of gender differences in how problematic behaviors may act as a gateway for developing other addictive behaviors. Taken together, these results represent important implications for assessing and treating online behavioral addictions.

Network Structure of Online Problematic Behaviors

Overall, the network of online behavioral addictions showed relative symptom sparsity after Least Absolute Shrinkage and Selection Operator regularizations, with only 17.9% of symptoms showing connections with other symptoms. While relationships between symptoms of different disorders were observed, stronger and more frequent relationships were observed between symptoms of the same disorder. For example, symptoms of disordered social media showed relationships with symptoms of disordered gaming and problematic internet use. Nonetheless, more frequent and stronger associations were observed between symptoms of disordered social media use. Interestingly, previous studies using regularized networks to assess symptoms of problematic behaviors similarly reported strong intra-disorder correlations between symptoms of problematic behaviors in online environments (Rozgonjuk et al., 2023; Zarate, Ball, et al., 2022). This notion adheres to previous studies suggesting the presence of uniquely distinct elements substantiating the emergence of different behavioral addictions and highlighting the need for further recognition in diagnostic and statistical manuals (Demetrovics & Griffiths, 2012; Griffiths, 2005).

Despite the observed intra-disorder symptom relationships, the network structure of problematic online behaviors provided evidence of connections between symptoms of different disorders, thus indicating the existence of coexisting problematic behaviors. Specifically, *Mood modification* related to online gaming (IGD Item-8) and internet use (IDS Item-8) were the most frequently connected bridge symptoms, and *Mood modification* related to internet use (IDS Item-8) and *Deception/Conflict* due to disordered internet use (IDS Item-7) showed the strongest connections with symptoms of other disorders.

These results align with the self-medication hypothesis suggesting that individuals predominantly engage in online activities to escape their problems or alleviate feelings of helplessness or anxiety (Khantzian, 1997). Indeed, recent studies observed that high distress (i.e., concurrent anxiety, depression, and stress) and withdrawal from real-life social situations significantly increased the risk of disordered online gaming (Kovacs et al., 2022). Thus, *Mood modification* to avoid distress or social isolation could increase the likelihood of transitioning into other problematic online behaviors. Moreover, studies reported that individuals might develop problematic behaviors such as online gaming (Gomez et al., 2018), problematic online shopping (Zarate, Fullwood, et al., 2022), or disordered online gambling (Stavropoulos, Monger, et al., 2022) to "escape" their problems (i.e., *Mood modification*). Finally, the results presented here support the hypothesized "digital convergence", suggesting that certain features of online platforms may facilitate further problematic online behaviors (Delfabbro & King, 2020). For example, "loot boxes" (i.e., prize features generated through a chance-based algorithm offered in online gaming platforms) and online gambling may facilitate similar neurological processes and cue reactivity and thus attract high-risk gamblers to gaming and vice versa (Gomez et al., 2022).

Developing Coexisting Online Problematic Behaviors

The longitudinal data set employed in this study assessed the influence that specific problematic behaviors may exert on other symptoms resulting in further problems. In this context, *Mood modification* related to disordered internet use, functional *Impairment* due to disordered gaming, and excessive preoccupation with gambling (*Salience*) assessed during the first wave of data collection were highly influential and frequently connected with problematic behaviors assessed during the second wave of data collection. In other words, individuals reporting these symptoms were more likely to experience further problems related to problematic online behaviors. Interestingly, these symptoms may represent different stages of disordered use (Griffiths, 2005). For example, while *Mood modification* may be the "gateway" to start engaging in problematic behaviors, *Salience* or *Impairment* may indicate advanced problematic behaviors associated with online BAs (Gomez et al., 2018; Stavropoulos, Monger, et al., 2022; Zarate et al., 2023). Finally, considering problematic behaviors at the disorder level, disordered gaming was the most influential, followed by disordered internet and social media use. This suggests that interest in exploring newly developed and attractive online games may develop in coexisting disordered online activity and thus result in further problematic behaviors (Anderson et al., 2017).

Gender Differences in Online Problematic Behaviors

Networks of problematic online behaviors in men and women showed invariant structure and global strength. In this context, structural and strength invariance across men and women indicate that these networks assess both population groups similarly and thus produce comparable results (van Borkulo et al., 2015). This finding partially contradicts past evidence suggesting a significantly higher propensity of online gaming and porn addiction symptoms among males and disordered social networking symptoms among females (Chen et al., 2017; Desai & Potenza, 2008; Pontes et al., 2019). However, the network invariance examination employed here constitutes a data-driven approach including all network nodes and edges (i.e., all technology addiction symptoms and their examined associations; Zarate, Ball, et al., 2022). Thus, rather than excluding gender differences, the present finding suggests that when examining proposed technology addiction-related behaviors, such gender differences may be deemed less important. Nonetheless, the current findings expand our current knowledge regarding gender-specific longitudinal symptoms and not syndrome centrality.

The most influential symptoms in men were *Loss of interest* in other activities due to disordered gaming and *Deception* due to disordered general internet use. Alternatively, the most influential symptoms in women were *Tolerance* and *Withdrawal* related to disordered social media use. These findings suggest that when examining concurrent symptoms of technology-related addictive behaviors, males who "lose their interest in other activities due to gaming" and "deceive others regarding their amount of internet use" are at higher risk of presenting concurrent technological addictions than males with other dominant symptoms (e.g., *gaming Preoccupation* or *Tolerance*). The same applies to females experiencing higher social media *Tolerance* and *Withdrawal* symptoms. Such findings align with the past literature indicating that while women may be at higher risk for disordered social media use, males are at higher risk for disordered online gaming, with these likely perpetuating other forms of technology-related addictions (i.e., one substituting the other, or engaging in addiction hoping behaviors; Su et al., 2020).

Besides examining influential symptoms for technology addiction manifestations, the present findings also detect the bridges, or connecting pathways, between different types of technology addictions and application-specific symptoms. Accordingly, when focusing on the influence of bridge symptoms in men, *Mood modification* related to internet use and *Tolerance* to gaming formed the most significant bridging point between disordered gaming and problematic internet use in general. Counterintuitively, when focusing on bridge symptoms in females, excessively thinking about gambling (*Salience*) in wave one was strongly connected with *Deception/Conflict* due to disordered online gaming in wave two (Table 1 and Supplemental File 2), revealing a female-specific addiction transition. Thus, the present findings expand the available knowledge regarding gender differences in vulnerability to technology addictions by identifying the importance of (a) gender-specific symptoms instead of syndromes; (b) gender-specific influential symptoms within the broader network; and (c) identifying different important connecting points (i.e., edges between symptoms) between males and females.

Implications, Limitations, and Conclusion

The study's findings have practical implications concerning the assessment and intervention of problematic online behaviors. First, the strong relationships between intra-disorder symptoms indicate that disorders assessed here reflect unique presentations of problematic behaviors. This suggests the need to detract emphasis from a diagnostic umbrella of "addictive behaviors" while moving toward recognizing each presentation as a separate diagnostic to effectively assess and address different addictive behaviors (Demetrovics & Griffiths, 2012; Griffiths, 2017). Second, the evidence reported here highlights the importance of addressing the compulsive need to engage in problematic behaviors to "escape" unwanted feelings or thoughts (Gomez et al., 2018; Stavropoulos, Monger, et al., 2022). Therefore, intervention strategies may identify peri-addictive factors motivating individuals to seek relief in online-related activity (Anderson et al., 2017). For example, identifying factors such as family cohesion or support networks may reveal significant individual motivations for disordered online activity and psychopathology (Gomez et al., 2021). Third, assessment and intervention strategies may consider how gendered presentations can affect the likelihood of transitioning between problematic behaviors, with men showing increased problems due to disordered gaming and women showing increased problems due to disordered social media use and excessive preoccupation with gambling. Finally, considering the possibility of translating a user's online behavior into health-related information, further assessment of digital footprints (i.e., residue of human–computer interaction) and problematic online behaviors could be implemented to detect and predict disorders such as anxiety, bipolar disorder, attention-deficit/hyperactivity disorder, etc. (Zarate, Stavropoulos, et al., 2022).

The study's results need to be interpreted in the context of important limitations. First, the sample used here included participants from developed countries and may not be generalizable to individuals living in nondeveloped countries. Second, the high percentages of missing data in responses to online gambling items may affect the structure of networks reported here, potentially limiting the generalizability of results. Third, the community sample used here may be representative of populations experiencing minimally impaired functioning due to disordered online activity. Finally, considering that the sample used had a higher share of men, results related to gender differences may need to be replicated in future studies using more gender-balanced samples.

The present study adds weight to the importance of identifying highly influential symptoms of online addictive disorders and their evolvement over time. Additionally, identifying specific gender differences in problematic online behaviors allows for added evidence to aid in accurate clinical diagnoses, targeted prevention, and treatment. Finally, identification and recognition of alternate BAs in diagnostic manuals are necessary for clinical diagnoses and early intervention screening; thus, this study adds to the empirical evidence required. It is hoped this research will assist in raising awareness of online BA comorbidity in the general population, accurate and timely screening and treatment of BAs, and adding to the empirical evidence essential for diagnostic manuals.

Supplementary Materials

docx	tmb0000105_supp001.docx	291 KB
pdf	open-practice-disclosure_Stavropoulos.pdf	138 KB

Received September 26, 2022
Revision received February 8, 2023
Accepted February 13, 2023

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