ORIGINAL ARTICLE

A Network Analysis of the Internet Gaming Disorder Scale–Short-Form (IGDS9-SF): An Intercontinental Large-Scale Study

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Abstract

The present study aimed to use a novel method (i.e., network analysis) to examine if the Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) has its unidimensional structure supported across different subgroups, including gender groups, continent groups, and age groups. Participants from five continents ($n = 545$ in Africa; $n = 27,910$ in Americas; $n = 4640$ in Asia; $n = 88,835$ in Europe; and $n = 1633$ in Oceania) completed the IGDS9-SF. The IGDS9-SF items showed a positively correlated network with moderate-to-high predictability (mean of $R^2 = 0.338$, SD $= 0.068$). Moreover, the network analysis results suggested that the IGDS9-SF is very likely to have a one-factor model. This one-factor model was further found to be invariant across gender groups (men vs. women), continent groups (Africa, Americas, Asian, Europe, and Oceania), and age groups (minor aged under 18 years, young adults aged between 18 and 30 years, and adults aged 30 years or above).

The Issue of Internet Use in the Current Era

In the new technology world marked by the impacts of the COVID-19 pandemic (Alimoradi et al., 2021, 2022; Chang et al., 2020, 2022; Chen et al., 2020a, 2020b; Hasannia et al., 2021; Liu and Arledge, 2022; Olashore et al., 2021; Prasiska et al., 2022; Rajabimajd et al., 2021), the entire world has been pushed to increased digitalization and virtual activities such as remote learning, working, and online shopping with increasing time spent online (Chen et al., 2021; Koch et al., 2020; Montag et al., 2024; Patel et al., 2020; Singh et al., 2020; Wilcha, 2020). Currently, most people around the globe, especially those residing in developed and modernized countries, are exposed to high levels of internet use due to increased penetration rates. Indeed, prior to the COVID-19 pandemic, internet accessibility was already high as more than half (i.e., 56.7%) of the entire global population were internet users in 2019 (The World

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Bank, 2022), with this figure still climbing up after the COVID-19 pandemic had been declared (i.e., 59.5% of the worldwide population were internet users in 2021; Johnson, 2021).

Problematic Gaming, Gaming Disorder, and Internet Gaming Disorder

Although positive features emerging from internet use and internet-related activities have been claimed (e.g., minimize the burden of physical restriction and time restriction) and designed (Drtilová et al., 2022; Nolan et al., 2012), it may be argued that a minority of the global population may develop serious health problems due to excessive internet use leading. More specifically, evidence has shown that a small portion of users are unable to resist their craving for engaging in excessive online usage (Kwok et al., 2021; Oluwole et al., 2021; Ranjan et al., 2021) and this might lead to addictive-like symptoms.

Among such online activities, gaming is the first activity that has been widely discussed in the literature, having been listed as a tentative mental health disorder in the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (DSM-5; American Psychiatric Association [APA], 2013) and as an official mental health disorder in the *International Classification of Diseases 11th Revision* (ICD-11; Gansner, 2019; Pontes & Griffiths, 2020; World Health Organization (WHO), 2018). Therefore, assessing gaming disorder (GD) (as termed by the WHO) or internet gaming disorder (IGD) (as termed by the APA) is deemed to be paramount for mental health professionals to assist individuals in improving their health and well-being during the COVID-19 pandemic and beyond.

Instrument Assessing IGD: Internet Gaming Disorder Scale–Short-Form (IGDS9-SF)

In addition to a formal diagnosis from a psychiatrist, the most cost-effective method to screen or diagnose IGD is by using a valid and short self-reported psychometric assessment test. To this end, numerous psychometric tests assessing IGD or GD have been developed, with promising psychometric properties being reported in the literature (Darvesh et al., 2020; King et al., 2020a, 2020b; Poon et al., 2021). Among these instruments, the IGDS9-SF (Pontes & Griffiths, 2015) was found to be one of the high-quality instruments assessing IGD with strong psychometric properties and much-needed brevity (King et al., 2020b).

More specifically, the IGDS9-SF contains nine items corresponding to the following diagnostic criteria for IGD as defined in the DSM-5 (APA, 2013): (i) preoccupation or obsession, (ii) withdrawal symptoms, (iii) tolerance, (iv) inability to control, (v) loss of hobbies other than gaming, (vi) persisting gaming engagement despite psychosocial problems, (vii) deceiving behaviors about gaming, (viii) using gaming as a negative coping method, and (ix) compromising important life events (e.g., occupation/education interruption). Moreover, a recent systematic review on the psychometric properties of the IGDS9-SF showed that it had satisfactory psychometric properties across more than 15 language versions (Poon et al., 2021).

However, according to the findings from Poon et al. (2021), the current psychometric evidence for the IGDS9-SF is primarily based on Classical Test Theory and secondary on Rasch models. Although such synthesized evidence supports the notion that the IGDS9-SF

presents with a unidimensional factor structure (Poon et al., 2021), to the best of the present authors' knowledge, there are two critical gaps in the literature regarding the psychometric properties of the IGDS9-SF which have not yet been addressed.

First, empirical studies assessing the psychometric properties of the IGDS9-SF only include regional participants (Poon et al., 2021). Although these empirical studies showed relatively consistent findings that the IGDS9-SF possesses promising psychometric properties (Poon et al., 2021), no direct comparisons across populations living in different continents have been carried out. Second, there is no research using another advanced statistical method (i.e., network analysis) to visualize the factor structure of the IGDS9-SF. To fulfill the scientific need to further investigate psychometric properties of an instrument from distinct perspectives, different statistical approaches should be employed (Lin et al., 2019). To this end, network analysis will provide a further perspective on the psychometric evidence of the IGDS9-SF.

Network Analysis

Network analysis, a statistical approach developed from social science, has the features of "structure, positions, and dyadic properties and the overall "shape" of ties on graph-theoretic properties" (Borgatti et al., 2009, p. 894). With the features, network analysis can quickly provide a visual model to construct, quantify, and describe the relationships between numerous variables that are of interest to researchers (Li et al., 2021). When using network analysis for psychometric instruments, the associations between instrument items can be quantified in a visualized method. Accordingly, the factor structure and psychological mechanisms examined using the instrument can be investigated as network analysis, which portrays how items of a given instrument are inter-related.

Although structural equation modeling or confirmatory factor analysis (CFA) can be used to provide quantitative evidence regarding the factor structure and psychological mechanisms of underlying constructs, such analyses (i.e., CFA or structural equation modeling) usually rely on complicated matrices for mathematical calculations and may encounter the problems of non-convergence (De Jonckere & Rosseel, 2022; McIntosh et al., 2014). In contrast, network analysis explores how the instrument items interact, without presenting with such limitations pertaining to convergence issue (Li et al., 2021). Moreover, explanations for the symptoms of a condition (e.g., how the nine IGDS9-SF items associate with each other to form a latent construct) can be appropriately outlined and modeled. As a result, some scholars have proposed using network analysis to supplement other statistical methods to provide useful and easy-to-understand information to also describe relationships between psychopathological constructs (Marcus et al., 2018; McNally, 2021).

The Present Study

Based on this, the present study had the following aims. First, it aimed to use network analysis to examine the factor structure of the IGDS9-SF across different intercontinental populations (i.e., Africa, Americas, Asia, Europe, and Oceania). Second, it aimed to examine if the factor structure concluded by the network analysis is invariant across different subgroups such as gender subgroups (i.e., men and women), continent subgroups (i.e.,

Africa, Americas, Asia, Europe, and Oceania), and age subgroups (i.e., minors aged below 18 years, young adults aged between 18 and 30 years, and adults aged 30 years or above).

Methods

Participants and Procedures

This study has utilized the data from a large international pool of gamers recruited from the "Smart Gaming" campaign, which comprises an independent study conducted via an online survey methodology through a platform developed by the leading researchers. Although this study was conducted in partnership with ESL Gaming within a corporate social responsibility framework aimed at educating gamers about their own gaming behaviors, the study was entirely independent, and the partner organization had no input in the study at all and the researchers received no direct or indirect compensation for conducting this study.

The data utilized in the present study included an initial sample of 192,260 self-reported gamers that was collected between January 2019 and February 2022; however, after employing data cleaning procedures, the final sample comprised 123,568 participants that were eligible for the analyses. The data cleaning process initially excluded participants that (i) did not provide parental consent ($n = 12{,}246$, 6.37%); (ii) were under 12 years of age ($n = 27{,}456$, 14.28%); (iii) reported being older than 80 years of age ($n = 196$, 0.10%); (iv) did not play video games in the last 12 months from the date of taking the survey ($n = 715$, 0.37%); (v) endorsed a sham item, i.e., reported playing a fictitious game ($n = 4974$, 2.59%); (vi) provided unreasonable amounts of time spent gaming, i.e., over 119 h a week, which assumes the average of 7 h of daily sleep a week ($n = 434$, 0.23%); (vii) reported playing more than 48 h during the weekend alone ($n = 918$, 0.48%); (viii) reported not being fluent in English language ($n = 16{,}314$, 8.49%); (ix) provided missing values ($n = 2$, < 0.01%); and (x) completed the survey during the COVID-19 pandemic in the years of 2020, 2021, and 2022 ($n = 5437$, 4.2%). Finally, to comply with the cross-cultural goals of the study, participants from five continents were subsampled as follows: $n = 545$ in Africa, $n = 27{,}910$ in Americas, $n = 4640$ in Asia, $n = 88{,}835$ in Europe, and $n = 1633$ in Oceania.

The study was granted ethical approval by the College Research Ethics Committee of Nottingham Trent University (2018/95). All participants were assured the data used for the analysis would be anonymous and confidential, and while participants aged between 12 to15 years were required to provide an electronic parental consent, those aged 16 provided an electronic informed consent to partake in the study. The aggregated data needed to replicate the present findings alongside the survey items are available on Open Science Framework (OSF) via the following link: https://osf.io/zdpt6/files/. No financial rewards were given to participants as they have received detailed anonymized normative feedback containing graphical and text-based data-driven insights into their own gaming behaviors in comparison to those who had completed the survey at that point in time.

Although the present study uses additional participants, the authors wish to disclose for the sake of transparency that the present work shows overlap to data with previous publications from this project—that included almost 10,000 less participants than the current study and only data from 2019—by Montag et al. (2021a) and Pontes et al.

(2022). Further works recently appeared (Maldonado-Murciano et al., 2022; Montag & Pontes, 2023; Montag et al., 2022; Pontes et al., 2024; Rozgonjuk et al., 2022). However, these earlier works investigated different research questions.

Internet Gaming Disorder Scale–Short-Form (IGDS9-SF)

The present study adopted the IGDS9-SF across all the studied countries. In brief, the IGDS9-SF contains nine items according to the nine IGD criteria defined by the DSM-5 (APA, 2013). The nine items were rated using a five-point Likert scale ranging from 1 (never) to 5 (very often) to indicate the frequency of a given description (e.g., "Do you feel preoccupied with your gaming behavior?") (Pontes & Griffiths, 2015). Total summed scores range between 9 and 45, with higher scores indicating more severe levels of disordered gaming. The promising psychometric properties (including evidence for a one-factor solution from CFA and Rasch models) of the IGDS9-SF in different language versions and across different populations have been summarized in a recent systematic review, which reported an internal consistency of Cronbach's α between 0.810 and 0.963 (Poon et al., 2021).

Statistical Analysis

Descriptive statistics were obtained for all variables and plots were examined. We applied regularized partial correlation networks (RPCNs; Epskamp et al., 2018) to explore relations among items without assuming latent structures. RPCNs apply the network analysis framework to psychological variables. Thus, network nodes (the basic components of the network) represent variables and edges (links between nodes) represent partial regularized correlations. Mathematically, RPCNs take a correlation matrix (in this case, polychoric correlations due to ordinal items) as input to partialize all correlations for all the other present correlations in the matrix (i.e., the rest of the items of the IGD9-SF). Then, it regularizes the false-positive rate of the network forcing near-zero correlations to zero, assuming them to be essentially uncorrelated. The standard estimation method is the Expected Bayesian Inference Criteria (EBIC) with the graphical Least Absolute Shrinkage Optimization (gLASSO) regularization. This method starts with a network estimated by the gLASSO and iteratively adds and removes edges until EBIC can no longer be improved. In addition, a proportion of explained variance for each node by the network can be obtained with an R^2 statistic. The final product of this process is a partial regularized correlation matrix, named "weight matrix."

As suggested by Mullarkey et al. (2018), we examined item standard deviations with an exclusion criterion of below 2.5 standard deviations of standard deviations since small-variance items can influence the final estimates of the network. Also, conceptually or empirically overlapping items can bias network estimations since they could measure latent traits without relevant, unique content. Therefore, we searched for empirically overlapped items with a three-step approach by (1) selecting pairs of items with potential conceptual overlap and estimated their correlations, (2) obtaining their mean and SD to form a criterion of 1 SD as empirically overlapping items, and (3) creating composite scores for each resulting pair, reducing the network. No items met our criteria. Then, we applied power and replicability analysis to examine the stability of the network. EBIC-gLASSO produced very high levels of sensibility and replicability indices, while specificity was not computed due to large sample size. We chose to use EBIC-gLASSO

over other methods due to offering equivalent results (see Supplementary Materials for details). To assess network replicability in depth, we also applied bootstrap techniques to the network. Among others, we implemented the correlation stability coefficient (CS) to assess stability of edges, with values above 0.25 as minimum and values above 0.5 as ideal (Epskamp et al., 2018). Once the replicability of the network is assessed, we proceed to represent the network graphically (see Fig. 1 for an example). We chose the Fruchterman-Reingold algorithm since it provides visually clear and intuitive displays (alternative methods of network plots are displayed in the Supplementary Materials).

Once the network is estimated, it is relevant to assess the relative importance of each node and possible groups of nodes. To explore groups of nodes (e.g., due to latent variables), we implemented exploratory graph analysis (EGA, Golino & Epskamp, 2017). This technique has shown comparable performance to traditional latent variable extraction methods, such as parallel analysis (Golino et al., 2020). Fourth, we also implemented a community analysis (mathematically equivalent to EGA) comparing other algorithms than the EGA's default (i.e., *walktrap*), like *spinglass* and multilevel. To assess replicability of EGA, we bootstrapped the EGAs. Entropy indices (Golino et al., 2021) were not considered due to bootstrapped EGA supporting the one-cluster structure in the 100% of the draws, leaving no room for comparison. Finally, we implemented an
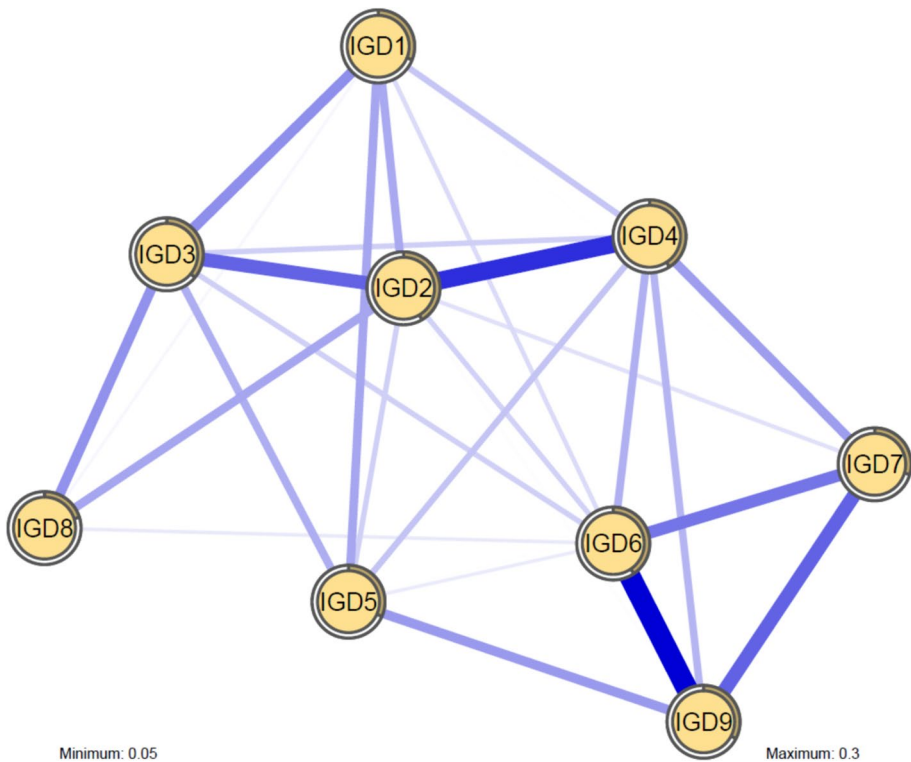

Fig. 1 Estimated network of the FFMQ with the one-factor solution using Fruchterman-Reingold method. Items are rounded in circles, with pies representing the explained variance (R^2) of each item. Lines connecting items represent correlations, blue = positive correlation, and red = negative correlation. Highly correlated items tend to be closer, while non-correlated nodes tend to be farther

exploratory factor analysis (EFA) for this sample as a comparison to RPCNs and EGA estimates with a more standard technique (see Supplementary Materials for details).

To explore the relative importance of each node, we implemented centrality analysis. Centrality involves the intensity (or "strength"), closeness, and interconnectivity (or "betweenness") of each node. All centrality indices were bootstrapped in the same way than edges.

To compare networks by gender, continents, and age groups, we estimated subset networks between men and women, between all continents, and between minors (< 18 years old), young adults (18–30 years old), and adults (> 30 adults). To do this, we implemented the joint graphical LASSO analysis, using the fused graphical LASSO estimation method (Borsboom et al., 2021; Costantini et al., 2017). This method allows to estimate a group of networks using a regularization on the differences of parameters across groups (an empirical example available in Fried et al., 2018). All subset networks were examined in power, replicability, and dimensionality with the same procedure as the overall network. In addition, all networks were bootstrapped to enable comparison. We discarded other analytic frameworks to do this (e.g., Network Comparison Test) due to having large sample sizes, making *p*-values too sensitive to non-meaningful deviations.

All analyses were computed using the R environment (R Development Core Team, 2020). Descriptive statistics were computed using *psych* (Rewelle, 2014), while the network analyses were computed using *bootnet* (Epskamp et al., 2018), *mgm* (Haslbeck & Waldorp, 2015), and *networktools* (Jones, 2020). The EGAs were computed using *EGAnet* (Golino & Christensen, 2019), the EFAs were computed using *psych*, and the CFAs were computed using *lavaan* (Rosseel, 2012). Joint graphical LASSO was estimated using *EstimateGroupNetwork* (Costantini et al., 2017).

Preregistration Information and Availability of Data and Materials

This study was not preregistered. Moreover, material and analysis codes for this study are available in the OSF (https://osf.io/zdpt6/files/).

Results

Item descriptive statistics showed relevant skewness for some items and samples, especially item 9 across all samples (Table 1). All items had means around 1 and 2.5 (i.e., low values) and SDs around 1. No items showed informativeness issues (i.e., none had SDs relevantly below the rest).

The IGDS9-SF items showed a positively correlated network (Fig. 1) with moderate-to-high predictability (mean of $R^2 = 0.32$, SD = 0.067). Bootstrap analysis revealed a stable network (see Supplementary Materials), with little differences between draws, stable behaviors in case drops, and correlation stability coefficients of 0.75, which are interpreted as stable.

In addition, multidimensional scaling plots showed little differences with the Fruchterman-Reingold network, allowing to use Fig. 1 as an interpretable spatial network. Centrality indices are displayed in Fig. 2. Items 2 (i.e., "Do you feel more irritability, anxiety or even sadness when you try to either reduce or stop your gaming activity?"), 6 (i.e., "Have you continued your gaming activity despite knowing it was causing problems between you and other people?"), and 4 (i.e., "Do you systematically fail when trying to control or cease

Table 1 Descriptive statistics of the IGDS9-SF

	Overall (N=123,568)		Men (N=114,473)		Women (N=9095)	
Items	Mean	SD	Mean	SD	Mean	SD
1	2.53	1.19	2.4	1.21	2.54	1.19
2	1.00[a]	1.00[a]	2.00[a]	1.00[a]	1.00[a]	1.48[a]
3	2.12	1.10	2.17	1.15	2.11	1.10
4	2.00[a]	1.00[a]	1.00[a]	1.00[a]	2.00[a]	1.00[a]
5	2.11	1.14	2.17	1.19	2.11	1.13
6	1.00[a]	2.00[a]	1.00[a]	2.00	2.00[a]	2.00[a]
7	1.00[a]	1.00	1.00[a]	1.00[a]	1.00[a]	1.00[a]
8	2.69	1.26	3.13	1.26	2.66	1.25
9	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]
	Africa (N=545)		Americas (N=27,910)		Asia (N=4640)	
Items	Mean	SD	Mean	SD	Mean	SD
1	2.72	1.24	2.58	1.23	2.79	1.17
2	2.00[a]	2.00[a]	2.00[a]	1.00[a]	2.05	1.03
3	2.35	1.20	2.16	1.15	2.37	1.12
4	2.00[a]	2.00[a]	2.00[a]	1.00[a]	2.03	1.01
5	2.33	1.24	2.27	1.19	2.21	1.16
6	2.12	1.32	1.00[a]	2.00[a]	2.22	1.17
7	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]
8	2.81	1.29	2.84	1.29	2.96	1.25
9	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]
	Europe (N=88,835)		Oceania (N=1633)			
Items	Mean	SD	Mean	SD		
1	2.49	1.17	2.93	1.20		
2	1.00[a]	1.00[a]	1.95	1.06		
3	2.09	1.08	2.15	1.14		
4	2.00[a]	1.00[a]	2.00[a]	1.00[a]		
5	2.05	1.11	2.31	1.18		
6	1.00[a]	1.00[a]	2.00[a]	2.00[a]		
7	1.00[a]	1.00[a]	1.00[a]	1.00[a]		
8	2.63	1.24	2.93	1.28		
9	1.00[a]	1.00[a]	1.00[a]	1.00[a]		
	Minors (N=21,168)		Young Adults (N=75,970)		Adults (N=26,430)	
Items	Mean	SD	Mean	SD	Mean	SD
1	2.5	1.21	2.58	1.2	2.39	1.14
2	2.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]
3	2.19	1.14	2.14	1.11	2.00	1.05
4	2.00[a]	1.00[a]	2.00[a]	1.00[a]	1.00[a]	1.00
5	2.07	1.17	2.11	1.14	2.14	1.10
6	2.00[a]	2.00[a]	2.00[a]	2.00[a]	1.00[a]	1.00[a]
7	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]
8	2.65	1.31	2.77	1.26	2.51	1.20
9	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]	1.00[a]

SD standard deviation. [a]Median and interquartile range since skewness is >|1| (items with medians but "SD" column without superscript display the SD due to median absolute deviation=0)

your gaming activity?") provided the highest values of strength, expected influence, closeness, and betweenness, followed by item 9 (i.e., "Have you jeopardized or lost an important relationship, job or an educational or career opportunity because of your gaming activity?") but with lower values. These results are compatible with the network plot, since
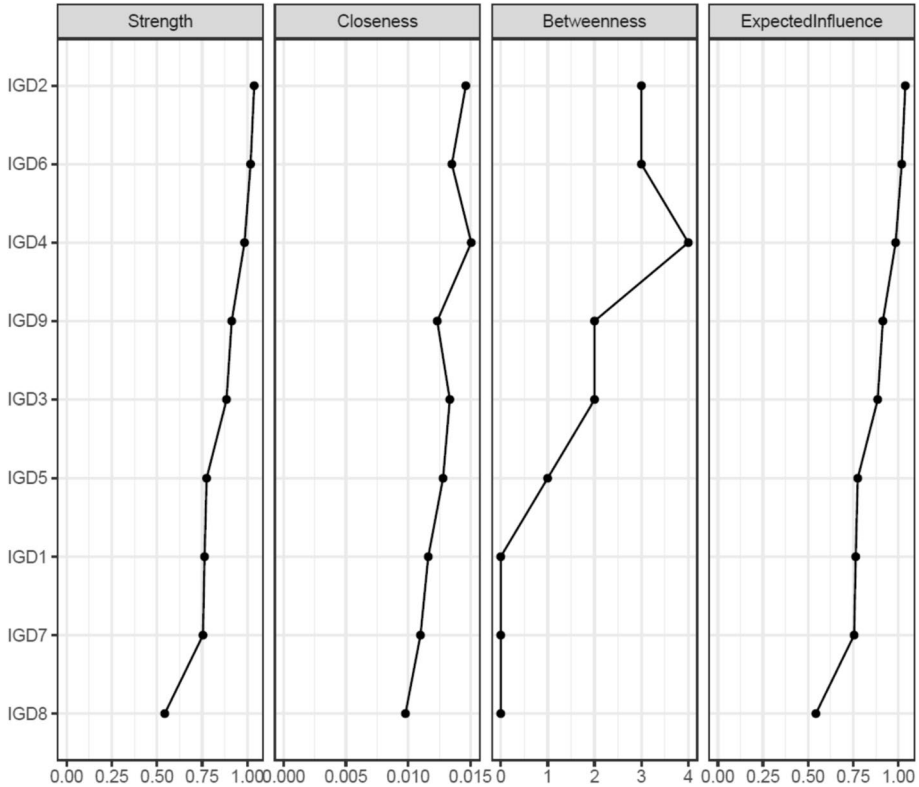

Fig. 2 Centrality indices for all items

items 2, 6, and 4 appear to be the more frequently and intensely connected items within the network, but also spatially more proximate to the center (item 9 is more peripheral). Therefore, it can be interpreted that these three items are the most central components in IGD as measured by the IGDS9-SF.

The default EGA supported the one-cluster model for the IGDS9-SF regardless of number of steps. The *spinglass* and *multilevel* algorithms supported instead a two-cluster solution, with items 6, 7, and 9 being a second cluster (named as "social impairment" component of disordered gaming). Nevertheless, bootstrap analysis provided a clear support for the one-cluster model, with 100% replications finding the same single community of items. Dimension and item stability analysis reported high stability for the one-cluster and all items.

Finally, the results of the EFA provided strong support for the one-factor model, with parallel analysis, fit indices, and factor loadings supporting this model, while the two-factor solution counted with mixed loadings and no support from parallel analysis. Thus, we interpret that the EGA and EFA strongly support the one-factor model. All in all, we consider that the estimated network is stable and supports the structure of one cluster or factor in disordered gaming.

Comparison of Networks

Power and replicability analysis obtained similar levels to the overall network in all samples. This is high levels of sensibility and correlation between samples, along with high levels of replicated parameters (see Supplementary Materials). Thus, all subset samples were stable and replicable. Regarding gender, males and females showed little or no differences in most edges. Figure 3 displays bootstrapped edges in both samples. Significant correlations (this is, non-overlapping confidence intervals) between males and females were mostly due to large sample sizes which enabled narrow confidence intervals, but with small effect sizes. In addition, both samples found strong support for a one-cluster solution (see Supplementary Materials). Thus, it can be interpreted than the IGDS9-SF seems to be mostly invariant regarding gender in its structure.

Regarding continents, Fig. 4 displays bootstrapped edges for Africa, Americas, Asia, Europe, and Oceania (sorted alphabetically). Edges displayed mostly the same values in all subsamples, with slight differences between them. Among them, Africa and Oceania showed broader confidence intervals, which is explained by their reduced sample size compared with the other continents. However, although some significant differences were found (i.e., non-overlapping confidence intervals), the differences were negligible (i.e., < 0.1 in weight) with no clear patterns between subsamples. In addition, dimensionality strongly supported the one-cluster solution, with all items
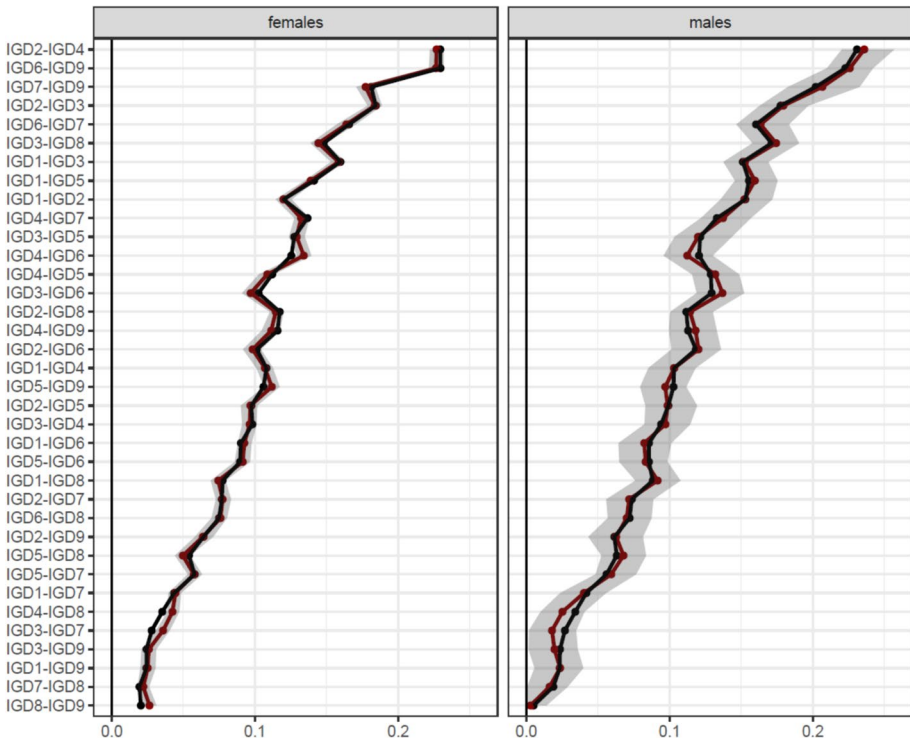

Fig. 3 Bootstrapped edges for networks of males and females. Shaded regions represent 95% confidence intervals for each measure
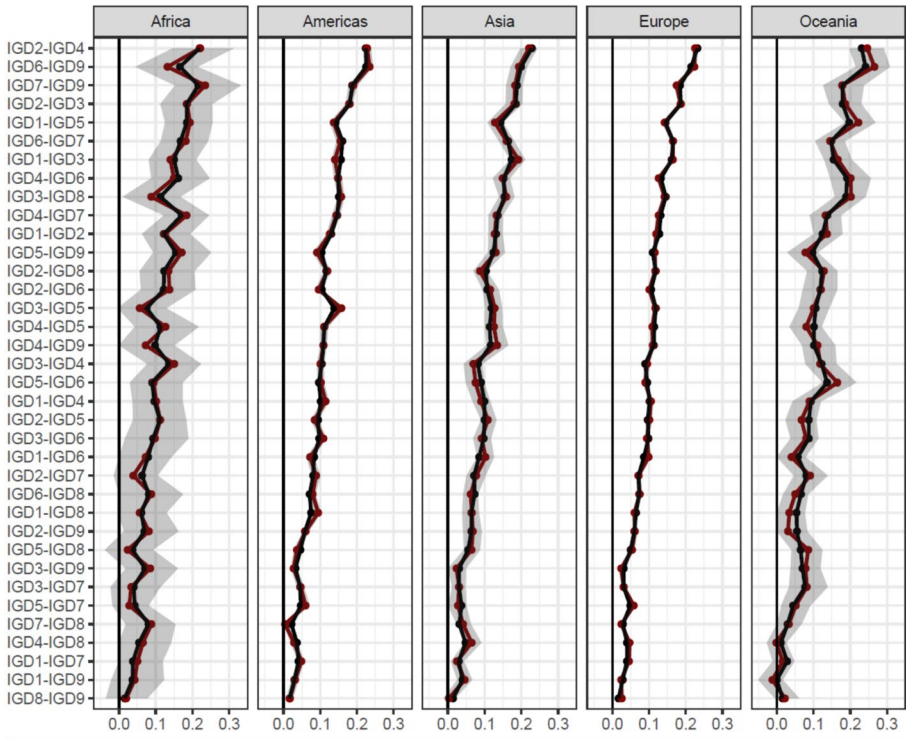
Fig. 4 Bootstrapped edges for networks of Africa, Americas, Asia, Europe, and Oceania. Shaded regions represent 95% confidence intervals for each measure

showing also strong support. Therefore, it can be interpreted that the IGDS9-SF is mostly invariant across continents.

Regarding age groups, Fig. 5 displays bootstrapped edges for minors (< 18 years old), young adults (18–30), and adults (> 30) age groups. Edges display mostly the same values with slight differences. In addition, dimensionality still is strongly supported as a one-cluster solution in all age groups, with all items showing strong support for this structure. Therefore, it can be interpreted that the IGDS9-SF is mostly invariant regarding age groups, with little differences between age groups.

The results encountered allow concluding that the IGDS9-SF displays a stable structure, but also seems invariant in structure and edges across genders, continents, and age groups. Thus, the overall network and its centrality indices can be used to interpret all subsamples (Fig. 1).

Discussion

With the use of a well-established psychometric method in the field of IGD, the present findings support the unidimensional structure of IGDS9-SF (APA, 2013; Pontes & Griffiths, 2015). Although prior ample evidence using different psychometric methods (including Classical Test Theory and Rasch models) (Poon et al., 2021) has demonstrated the solid
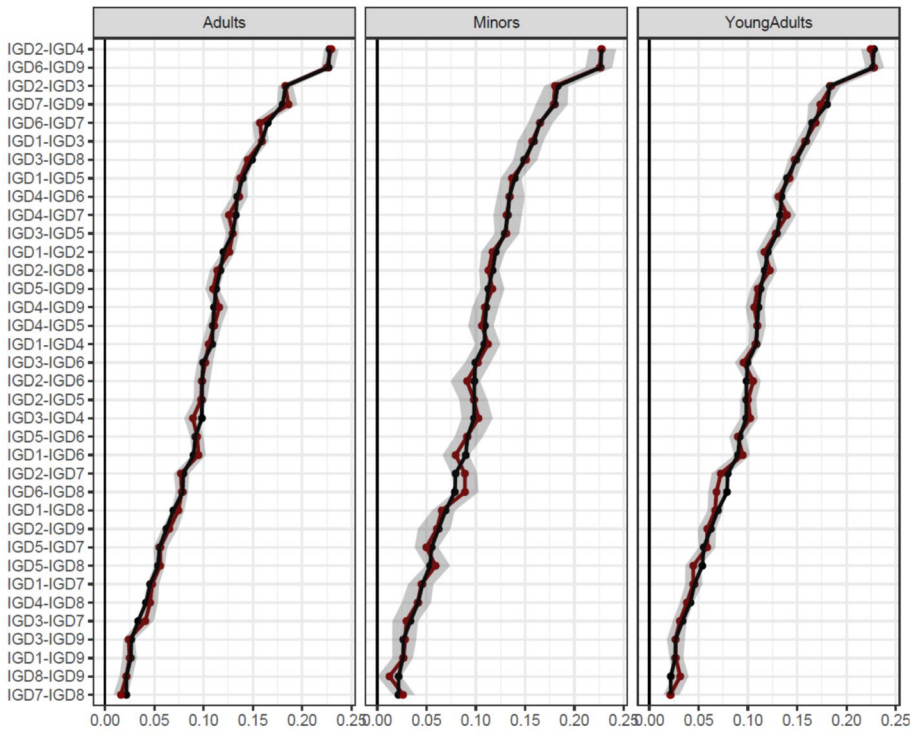
Fig. 5 Bootstrapped edges for networks of minors (< 18 years old), young adults (18–30 years old), and adults (> 30 years old). Shaded regions represent 95% confidence intervals for each measure

psychometric properties of the IGDS9-SF, to the best of the present authors' knowledge, the IGDS9-SF has never been evaluated using network analysis. Therefore, the promising findings from this study add to the literature testing the psychometric properties of the IGDS9-SF.

Importantly, the present findings echo prior findings using other psychometric testing methods (Poon et al., 2021), allowing the conclusion that the IGDS9-SF has a stable factor structure that is invariant in terms of structure and edges across genders, continents, and age groups. In other words, the overall network and its centrality indices can be used to interpret all subsamples. Therefore, the findings obtained corroborate the suggestion from King et al. (2020b) that IGDS9-SF is one of the best instruments assessing IGD.

The unidimensional structure of the IGDS9-SF verified by the present findings and prior research findings (Poon et al., 2021) supports the fact that the nine criteria defined by the DSM-5 (APA, 2013) are coherently and highly associated with the concept of IGD. This piece of evidence contradicts the prior notion that excessive online behavior can take place in specific areas such as gaming. Nevertheless, the literature also proposes that problematic use of the internet may be observed in two forms: either a generalized form of problematic use (e.g., a person overuses several online channels) or a specific form problematic use (e.g., gaming that was examined in the present study) (Chen et al., 2020a, 2020b, 2020b; Leung et al., 2020; Montag et al., 2015; Pontes, et al., 2015).

Although psychometric evidence of the IGDS9-SF has been synthesized by a systematic review (Poon et al., 2021) using the rigorous COnsensus-based Standards for the selection of health Measurement INstruments (COSMIN) method (Mokkink et al., 2020; Prinsen et al., 2018), the COSMIN method does not consider network analysis. Moreover, Poon et al. (2021) found that the existing psychometric evidence for the IGDS9-SF was primarily based on Classical Test Theory with some based on Rasch models highlighting the fact that there is a lack of psychometric evidence using a straightforward and visualized method (i.e., network analysis) for the IGDS9-SF. Given that the scientific nature for establishing a robust instrument is to use different methods to repeatedly test its psychometric properties (Lin et al., 2019), the present study filled in the literature gap regarding evidence from network analysis on the unidimensional structure of IGDS9-SF.

Apart from using a new method to test the unidimensionality of the IGDS9-SF, the present study extends the findings from previous research focusing on regional populations to cross-country populations. More specifically, prior evidence on the IGDS9-SF did not take into account participants from large samples across different continents. The present study recruited participants from five continents with large sample sizes. With the large sample sizes across different continents being included in this study, the findings regarding unidimensional structure of the IGDS9-SF with supported invariance could be considered stable. Future studies can thus use the IGDS9-SF to investigate disordered gaming and related issues (e.g., effectiveness of intervention programs on IGD, phenomenal studies on how IGD associates with other health outcomes).

There are some limitations in the present study worth mentioning. First, we did not investigate other external criteria measures associated with IGD (e.g., psychological distress) (Chen et al., 2020a, 2020b, 2020b). Therefore, it remains uncertain if the IGDS9-SF, as assessed through the current network analysis, possesses sufficient properties to correlate with these pertinent concepts or health outcomes; however, assessing the associations between external criteria measures and IGD was beyond the scope of this study. Moreover, prior studies from the same data pool showed that the IGDS9-SF was associated with personality (Montag et al., 2021b), time spent gaming (Pontes et al., 2022), and importantly, self-reported functional impairments across different areas of life (Montag & Pontes, 2023; Pontes et al., 2024). Therefore, this limitation can be tentatively classed as not serious. Second, although the samples recruited across the five continents are a strength in the present study, the sample sizes were unbalanced across the five continents. More specifically, participants from Africa comprised less than 1000 individuals, which might not be directly comparable to the other continents. The disparity in sample sizes might stem from the method of data collection, primarily snowball sampling. Nonetheless, concerns regarding network stability and power are not significant, considering the power analyses conducted on our networks along with bootstrap stability assessments. Moreover, networks and EGAs seem stable for these sizes, leaving concerns of generalizability towards improved sampling methods in future studies. Third, there were no re-test data for the IGDS9-SF. Therefore, it is unsure whether the same network could be replicated in a re-test sample. Future studies are thus warranted to examine the stability of the factor structure of IGDS9-SF using next network analysis. Lastly, the present study did not collect participant characteristics other than gender, continent (inferred from self-reported country), age, educational level, and employment status. However, we considered that gender, continent, and age were the most relevant variables for the present study. Nevertheless, future studies may consider testing the IGDS9-SF in other characteristics (e.g., educational level).

Conclusion

In summary, the results reported showed that the IGDS9-SF is an adequate instrument for assessing the construct of IGD based on the DSM-5 criteria for IGD. The construct of IGD as measured by the IGDS9-SF could be unidimensional and invariant across different subgroups, including gender subgroups (men and women), continent subgroups (Africa, Americas, Asia, Europe, and Oceania), and age subgroups (minors aged below 18 years, young adults aged between 18 and 30 years, and adults aged 30 years or above). Based on the present findings, future research can use the IGDS9-SF to perform comparisons across multiple countries, different genders, and various age groups, building upon the present study. Finally, the main research implications of the present study include the following aspects: (i) the IGDS9-SF could be a useful instrument assessing IGD in large cross-cultural research that includes different continents; (ii) the IGDS9-SF could help quickly identify people having high levels of IGD regardless the person's gender, living area, or age.

Author Contribution Conceptualization—OL, C-YL, CM, HMP, and AHP.
    Data curation—OL and AHP.
    Formal analysis—OL and AHP.
    Investigation—CM and HMP.
    Methodology—CM and HMP.
    Project administration—CM and HMP.
    Resources—OL and AHP.
    Software—OL and AHP.
    Supervision—CM, HMP, and AHP.
    Validation—C-YL, CM, HMP, and AHP.
    Visualization—OL.
    Writing (original draft)—OL, C-YL, and AHP.
    Writing (review and editing)—CM and HMP.
    All authors have reviewed and agreed to their individual contribution(s) before submission.

Data Availability Material and analysis codes for this study are available in the OSF (https://osf.io/zdpt6/files/).

Code Availability Material and analysis codes for this study are available in the OSF (https://osf.io/zdpt6/files/).

Declarations

Conflict of Interest The authors report no conflict of interest. However, for reasons of transparency Dr. Montag mentions that he has received (to Ulm University and earlier University of Bonn) grants from agencies such as the German Research Foundation (DFG). Dr. Montag has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from gaming or social media companies. Dr. Montag mentions that he is part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-digitalitaet-und-verantwortung/) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he receives no salary for his activities. Finally, he mentions that he currently functions as independent scientist on the scientific advisory board of the Nymphenburg group. This activity is financially compensated. Moreover, he is on the scientific advisory board of Applied Cognition (Redwood, CA, USA), an activity which is also compensated.

Ethics Approval The study has received ethical approval by the research team's University Ethics Committee (College Research Ethics Committee of the Nottingham Trent University [2018/95]). All participants were assured the data used for the analysis was anonymous and confidential.

Consent to Participate All the participants provided informed consents.

Consent for Publication Not applicable.

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