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Disordered Gaming: The Role of a Gamer's Distress Profile

Jade Kovacs[1], Daniel Zarate[1], Gabriel de Sena Collier[1], Thong Thai Diep Tran[1] & Vasileios Stavropoulos[1,2]

[1]College of Health and Biomedicine, Victoria University; [2]University of Athens

Abstract

Background: Internet Gaming Disorder (IGD) embodies a persistent and recurrent engagement with video games, to the exclusion of other activities, that cannot be controlled, and with significant impairments in everyday functioning. Previous research suggests that IGD is experienced differently depending on the gamer's profile, while distress symptoms such as depression, anxiety, and stress have been independently associated with the development of IGD. Interestingly, no study to date has aimed to profile gamers based on these three psychopathologies. The present study aimed to (1) profile gamers concerning their depression, anxiety, and stress, and (2) examine the differences in IGD levels between the different profiles of distress. **Method**: A sample consisting of 968 gamers (18-64 years, Mage = 29.54) was assessed with the Depression, Anxiety and Stress Scale (DASS-21) and the Internet Gaming Disorder Scale-Short-Form (IGDS9-SF). **Results**: Latent profile analysis (LPA) identified 3 distinct distress profiles. These encompassed 'High-Distress Comorbidity' (HDC; 25.9%), 'Medium-Distress Comorbidity' (MDC; 48.7%), and 'Low-Distress Comorbidity' (LDC; 25.4%) gamers. As hypothesized, higher distress comorbidity profiles are linked with higher IGD levels. **Discussion**: Findings suggest that different distress profiles vary by symptom severity. The HDC profile was characterized by higher levels of anxiety, depression, and stress, and associated with a higher level of IGD symptoms. Therefore, individuals displaying IGD difficulties appear to concurrently suffer from anxiety, depression, and stress, which should be targeted concurrently.

Keywords: Anxiety, Depression, Internet Gaming Disorder, Latent Profile Analysis, Stress

1. Introduction

Internet Gaming has attracted research interest due to its prevalence among all age groups and its potential effects on psychological health and wellbeing (Anderson et al., 2017; Stavropoulos et al., 2018; Stavropoulos et al., 2019). Previous research has shown that gaming can facilitate a wide range of cognitive, therapeutic, and social benefits (Granic et al., 2014; Raith et al., 2021). However, excessive gaming has been associated with anxiety, depression, obsessive-compulsive behaviour, attention deficit/hyperactivity, social phobias, and loneliness (Männikkö et al., 2020; Tullett-Prado et al., 2021; Wong et al., 2020). These negative repercussions have prompted scholars to introduce diagnostic classifications related to disordered gaming (Stavropoulos et al., 2020). For example, in 2013, the American Psychiatric Association (APA) included Internet Gaming Disorder (IGD) in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) under Section III as a condition warranting more clinical research and experience before it may be considered as a formal disorder in the primary manual (DSM-5, APA 2013). Five years later (2019), Gaming Disorder (GD) was recognized as an official classification in the 11th edition of the International Classification of Diseases (ICD-11) by the World Health Organization (WHO, 2019).

According to the DSM-5, IGD consists of nine core symptoms with at least five of these present over 12-months (APA, 2013). These nine clinical symptoms are 1: a preoccupation with videogames (preoccupation); 2: withdrawal symptoms (e.g. irritability and frustration) in the absence of gaming (withdrawal); 3: the need to spend an increased amount of time playing videogames to create the same “high” (tolerance); 4: an inability to control how much time is spent playing videogames, even when the subject wants and attempts to (loss of control); 5: a loss of interest in previously enjoyed activities (other than gaming) as a consequence of videogames (surrendering from other activities); 6: continuing to play videogames despite understanding their negative effects (continuation); 7: deceiving those close to them, therapists or others regarding their gaming habits (fraud); 8: utilizing videogames to deal with or eliminate negative feelings (escape), and finally; 9: damage or loss of relationships, work or education as a result of videogame engagement (negative consequences-reducing one's everyday life functionality).

1.1 Conceptualization of disordered gaming

Individual differences interwoven with different risk profiles have been suggested to contribute to the development of IGD. Particularly, distress symptoms such as depression and anxiety (along with other factors) may act as risk factors for IGD (Burleigh et al., 2018; Liew et al., 2018; Stavropoulos et al., 2021a). There have been many explanatory proposals put forward to understand how such individual differences may interact with each other in relation to IGD (Brand et al., 2016; Davis, 2001; Griffiths, 2005; Griffiths et al., 2017; Kardefelt-Winther, 2014). For example, the self-medication hypothesis (Khantzian, 1997) has been adopted to understand behavioural addictions including IGD and posits that distressed individuals may engage in problematic online gaming as a means of relief (Griffiths, 2005; Griffiths et al., 2017). Similarly, the Compensatory Internet Use (CIU) model (Kardefelt-Winther, 2014) suggests that disordered gaming may be a coping strategy to manage psychopathological symptoms or negative life events (although concerns regarding the over pathologizing of common behaviours have been raised; Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). Much like the self-medication hypothesis, this model posits the idea that addictive use of the internet may help one cope with their psychological suffering such as anxiety, depression, and stress (Griffiths, 2005; Griffiths et al., 2017).

While aetiological models (e.g., CIU) provide useful potential explanations, many researchers have suggested an alternative 'typological' approach to understanding the patterns in which IGD may manifest (Billieux et al., 2015; Colder Carras & Kardefelt-Winther, 2018; Faulkner et al., 2015; Lee et al., 2017; Lemmens et al., 2015; Pontes et al., 2014; Tullett-Prado et al., 2021; Ünübol et al., 2020). This approach focuses on identifying variability across different profiles of gamers based on IGD symptoms or behaviours to better understand the gamers' context (Stavropoulos et al., 2020; Stavropoulos et al., 2021).

Such variability among gamers' profiles has been observed via latent profile analyses (LPA) considering IGD-related symptomatology (Billieux et al., 2015; Colder Carras & Kardefelt-Winther, 2018; Faulkner et al., 2015; Lee et al., 2017; Lemmens et al., 2015; Pontes et al., 2014; Tullett-Prado et al., 2021; Ünübol et al., 2020). For example, Pontes and colleagues (2014) used the 20-item IGD and identified 5 distinct profiles in a population of gamers (n=1003) where profiles varied according to symptom severity and gameplay hours (i.e., casual, regular, low-risk, high-risk and disordered gamers). Similarly, Colder Carras and Kardefelt-Winther, (2018) used the Assessment of Internet and Computer game Addiction-Gaming Module on a population of 7865 adolescent gamers from Europe and identified 5 varying profiles of gamers (i.e., normative, IGD, concerned, at risk, engaged). Interestingly, both anxiety and depression significantly predicted membership of the IGD "engaged" and "concerned" profiles. Lemmens et al. (2015) utilized the Internet Gaming Disorder Scale-Short-Form and identified 3 profiles (e.g., normal, risky, disordered) based on time spent gaming, self-esteem, loneliness, and aggression. Additionally, Faulkner and colleagues (2015) utilized the Problem Video Game Playing Scale on a population of 3338 high-school students in the USA aged between 11-20 years. Informed by the severity of problematic gaming they identified four profiles (e.g., normative, low, high, severe). Students in the severe profile had significantly more depression and anxiety symptoms than students in the high, low, and normative profiles. While these profiles have been observed considering IGD-related symptomology, they have not been described/portrayed, to the best of the author's knowledge, on the basis of one's comorbid distress symptoms as potential risk for the development of IGD.

1.2 Distress and disordered gaming

Consistent with the forementioned self-medication (Khantzian, 1997) and Compensatory Internet Use (Kardefelt-Winther, 2014) models, "negative escapism" suggests gaming is negatively reinforced as a means of avoiding symptoms of distress (Martín-Fernández et al., 2017). Indeed, individuals with depression, anxiety, or stress may spend excessive time gaming on the internet as a coping mechanism to deal with worries and difficulties in their life (Ho et al., 2014; Yen et al., 2019). Similarly, IGD and low mood may often present with several behaviours in common, including social withdrawal, fatigue, disruption of sleep, and poor performances in school and work (Achab et al., 2011).

Subsequently, in terms of IGD comorbidities, depression, anxiety and stress are among the most frequently reported health-related variables associated with IGD (Darvesh et al., 2020; Wong et al., 2020). A recent meta-analysis investigating depression in individuals diagnosed with IGD observed that the comorbidity of depression in individuals with IGD ranged up to 75% with an average prevalence of 32% (Ostinelli et al., 2021). Similarly, a meta-analysis examining the relationship between IGD and comorbid psychopathologies, found that 92% (out of 13) of studies involving anxiety, described significant positive correlations between anxiety and IGD (González-Bueso et al., 2018). Furthermore, stress has also been shown to have a strong association with IGD suggesting that stress is a risk factor for addiction and increases the likelihood of relapses (Goeders, 2003; González-Bueso et al., 2018; Stavropoulos et al., 2021b).

1.3 Current study

The above-described research indicates a relationship between psychological distress and IGD, however the details of this relationship are not yet entirely elucidated. In particular, the degree to which the individual facets of psychological distress are seen in individuals of varying IGD experience has yet to be examined. Given the connection between distress and IGD, and the heterogeneity of IGD experience, this makes a worthwhile avenue of investigation into the risks and consequences of IGD. This is particularly beneficial as comorbid psychopathology may require to be treated concurrently with IGD for optimum results (Zajac et al., 2020).

Accordingly, the present study aspires to address the following. Firstly, to advance past knowledge considering the typologies/profiles of distress symptoms within the gaming population. (e.g., can an online community sample of gamers be described by different distress profiles/typologies?). Secondly, to expand the empirical evidence considering distress symptoms as potential IGD aetiology (e.g., is there a significant difference in IGD levels between the different profiles of distress?). These aims will be innovatively addressed by the examination of a large cohort of gamers (*N* >900), the use of a psychometrically sound and broadly used distress scale (i.e., Depression, Anxiety and Stress Scale, 21 items; DASS-21; Lovibond & Lovibond, 1995) and the implementation of a statistically advanced sequence of 12 potential profiling models (Rosenberg et al., 2019). Accordingly, to address the outlined aims, the following research questions were elaborated:

RQ1: What is the number and nature of distress profiles that best describes the cross-sectional sample examined, taking into consideration levels of depression, anxiety and stress?

RQ2 – What is the proportion of individuals in each profile based on the selected indicators?

Additionally, the following hypothesis was elaborated:

H1– Participants experiencing higher levels of distress will display higher levels of disordered gaming.

2. Method

2.1. Participants

An online community sample of English speaking, adult gamers aged 18 to 64 were included in the study. The initial sample comprised 1097 responses, with 7 participants deleted due to being preview-only responses, 5 deleted after being flagged as spam responses, and 11 deleted due to being potential bots, 11 deleted as they did not provide consent to participate in the study, 16 were deleted for not providing their age, 2 were deleted for being younger than 18, and a further 77 were excluded due to providing minimal responses to the battery of questionnaires. After this data screening process, the sample consisted of N=968, M_{age}=29.54, SD_{age}=9.35, Males=622 (64.3%), Females=315 (32.5%), other=31 (3.2%, including trans/non-binary, genderqueer). Missing values in participants' responses represented 0.12% and were below recommended thresholds (>5%; Schafer, 1999) and missing completely at random (MCAR; Little's test χ^2 = 314.979, *df* = 281, *p* = .080). Therefore, we proceeded with the analyses. Table 1 shows participants sociodemographic information.

-Table 1-

2.2. Measures

Depression, Anxiety and Stress Scale (DASS-21) was utilized to assess, via self-reporting, depression, anxiety, and stress with seven items for each self-report subscale (Lovibond & Lovibond, 1995). The 21 items are rated on a four-point Likert scale ranging from 0 to 3 with a total score for each subscale ranging between 0 and 21. Examples of items include *"I found it hard to wind down"*. Higher DASS scores indicate a higher level for that corresponding subscale. The DASS-21 has showed excellent internal reliability (Cronbach's α = 0.81, 0.89 and 0.78; Coker et al., 2018) and appropriate convergent validity (Le et al., 2017) in previous research and the present study (Stress Cronbach α = .883, and Mc Donald's ω = .883, anxiety α= .865, ω = .869 depression α= .931, and ω = .932 and for the whole scale (distress factor) α= .950, and ω = .950).

Internet Gaming Disorder Scale-Short-Form (IGDS9-SF; Pontes & Griffiths; 2015) is a short psychometric self-report tool to examine, via self-reporting, online and offline gaming activities within the last 12 months. The 9 items are measured on a 5-point Likert scale ranging from 1 (Never) to 5 (Very Often) with total scores ranging from 9 to 45, and higher scores indicating higher levels of IGD. Examples of items include *"Do you feel preoccupied with your gaming behavior"*. The IGDS9-SF shows acceptable internal reliability with a Cronbach's alpha of 0.87 (Revelle & Condom, 2019), as well as high convergent validity (Kim & Ko, 2020). For the present study, the internal reliability rate of the scale was Cronbach α= .885, and Mc Donald's ω = .892.

2.3. Procedure

Upon obtaining approval from the Victoria University Human Research Ethics committee (HRE20-169), participants were recruited through convenience sampling. A Qualtrics link was distributed through social media platforms. The survey was targeted towards gaming populations by using keywords such as Internet games, PC gamer, MMORPGs, MOBA's, FPS. Upon accessing the link, participants were directed to the Plain Language Information Statement clearly stating the study aims, potential contributions, voluntary participation, right to withdraw and informed consent. Informed consent was assured as participants were required to tick a box prior to beginning the survey. Considering that the current study aimed to protect participants from inadvertent harm, all participant information remained anonymous with individual participants only being identifiable by number.

2.4. Statistical analyses

To address RQ_1 and RQ_2, the depression, anxiety, and stress subscales as assessed by the DASS-21 were employed as indicators for a Latent Profile Analysis (LPA) using the TIDYLPA CRAN package in R (Rosenberg et al., 2019). This analysis was chosen for its modelling approach which allows for the identification of naturally homogenous subgroups (profiles) within a population based on descriptors or characteristics of significance (Muthén & Muthén, 2016). Specifically, LPA employs a Maximum Likelihood Estimator (MLE) to identify profile membership probabilities among gamers based on their distress symptoms. TidyLPA was selected for its ability to estimate optimal relationships between indicators across different profiles, including means (i.e., average levels of DASS), variances (i.e., variability of DASS within profiles), and covariances (i.e., variability of DASS across profiles; Tullett-Prado et al., 2021). Table 2 below shows the four possible combinations of parameterizations of variance-covariance structures that can be estimated with TidyLPA to obtain the optimal number of profiles (for a thorough explanation see Masyn, 2013, page 585).

-Table 2-

Selecting the optimal number of latent profiles involved a sequential process. Firstly, identification of the best combination of parameters (including (un)constrained profile mean, variance, and covariance) by comparing models based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Approximate Weight of Evidence Criterion (AWE), Classification Likelihood Criterion (CLC), and Kullback Information Criterion (KIC) with smaller values indicating better fit (Masyn, 2013). Secondly, assessing the best number of profiles via the bootstrapped likelihood ratio test (BLRT) to determine if adding an extra latent profile resulted in a significant increase in fit (with $p < .05$ as indication of improved fit; McLachlan, 1987). Finally, evaluation of standardized entropy criterion (*h*) to assess heterogeneity levels across latent profiles, with 0.40-0.60 indicating low, 0.60-0.80 medium, and > .80 high entropy (Celeux & Soromenho, 1996; Clark & Muthén, 2009).

Additionally, to address H_1, a one-way ANOVA was conducted to examine the difference in IGD scores between the different distress profiles. Further post hoc analyses were conducted to examine where these differences lied.

3. Results

3.1 Identifying and describing distress profiles

To answer *RQ1* and *RQ2*, we sought to identify the optimum number of latent profiles and the population share in each profile. Table 3 shows initial testing of 24 possible combinations of models, varying by number of classes and parametrization. The Class Variant Diagonal Parameterization (CVDP) model with 3 profiles and the Class Variant Unrestricted Parameterization (CVUP) model with 2 profiles were further examined due to their lower AIC and BIC values.

-Table 3-

Table 4 shows further testing to expand fit indices for the CVDP model with 3 profiles and the CVUP model with 2 profiles (Rosenberg et al., 2019). Both options showed significant BLRT-p and an appropriate number of participants in the smallest latent profile. While the CVUP model with 2 profiles yielded superior AIC and BIC, the CVDP model with 3 profiles resulted in better level of classification accuracy (entropy = 0.84) and was therefore selected due to optimum fit. Observed entropy for this model significantly exceeded the cut-off point of 0.76 (Larose et al., 2016), suggesting that the accurate classification of the CVDP

3-profile structure was over 90% correct (Larose et al., 2016). Accordingly, the share of participants in each estimated profile were *n* = 251 (25.9%) for Profile 1, *n* = 471 (48.7%) for Profile 2, and *n* = 246 (25.4%) for Profile 3. Table 5 displays the profiles standardized mean scores, raw mean scores and standard deviations of depression, anxiety, and stress.

-Table 4/Table 5-

Distress latent profiles were described considering both raw and standardized reported symptoms to examine their distinct features while concurrently enabling objective understanding in the terms of normal distributions of depression, anxiety, and stress (*RQ1)*. In that context, the three latent distress profiles showed variability in raw scores and mean values of depression, anxiety, and stress levels. Figure 1 illustrates mean differences in distress symptoms across latent profiles, and Figure 2 compares raw distress symptoms with normal population scores (as suggested by Coker et al., 2018). Individuals classified in **Profile 1** scored in the 'extremely severe' range for depression (14+) and anxiety (10+), 'severe' range for stress (13-16), and scored +1.15SD to +1.26SD with respect to mean distress values for our sample. Consequently, Profile 1 was defined as "High-Distress Comorbidity" (HDC), distinguished by the highest distress symptoms. Participants in **Profile 2** scored in the 'moderate' range for depression (7-10), 'mild' range for anxiety (4-5), 'normal' range for stress (0-7), remained near mean distress levels **(-**0.17SD to -0.05SD), and were thus labelled "Medium-Distress Comorbidity" (MDC). Finally, participants in **Profile 3** scored in the 'normal' range for depression (0-4), anxiety (0-3), stress (0-7), and scored below mean levels (-1.10SD to -0.92SD). This profile was thus defined as the "Low-Distress Comorbidity" profile (LDC), distinguished by the lowest symptom experiences when compared to the other distress profiles.

-Figure 1/Figure 2-

3.2. Hypothesis 1: distress profiles and IGD

With alpha set at .05, a one-way ANOVA without assuming homogeneity of variance (i.e., Welch's test) was conducted to examine the differences between IGD scores within Profile 1 (HDC), Profile 2 (MDC), and Profile 3 (LDC). The results indicated that there was a significant and large effect on IGD scores between the different profiles, F_{Welch} (2,528.15) = 101.94, $p < .001$. Games-Howell post-hoc analyses revealed that the differences in IGD were significant across all three different profiles (High distress to Mid distress; $p < .001$; *SE*: .59; CI: 2.03 - 4.85; High distress to Low distress; $p < .001$; *SE*: .59; CI: 6.32 – 9.14; Mid distress to Low distress; $p < .001$; *SE*: .42; CI: 3.31 – 5.28). In other words, the mean IGD scores within the profiles steadily decreased in descending order of HDC, MDC, and LDC (see Figure 3). Interestingly, those belonging to the "High-Distress Comorbidity" profile also displayed a tendency to score higher in IGD compared to individuals in other profiles (observed by elevation and size of dots). This supports our hypothesis indicating that profiles with concurrently higher depression, anxiety and stress are accompanied by higher levels of IGD.

-Figure 3-

4. Discussion

The present study was the first to examine distress profiles in a large sample of 968 gamers. This was done via the use of a psychometrically sound and broadly used distress scale (i.e., Depression, Anxiety and Stress Scale) and the implementation of a statistically advanced sequence of 24 potential profiling models (Rosenberg et al., 2019). Findings suggested the presence of three distinct distress profiles. These encompassed 'High-Distress Comorbidity' (HDC; 25.9%), 'Medium-Distress Comorbidity' (MDC; 48.7%) and 'Low-

Distress Comorbidity' (LDC; 25.4%) gamers. As hypothesised, higher distress comorbidity profiles were associated with higher IGD levels.

4.1 Different distress profiles among the gaming population

The findings suggested three distinct profiles of distress present within this gaming population. The depression, anxiety, and stress levels within each profile were qualitatively different. Specifically, participants in the HDC profile showed severe stress, extremely severe depression, and anxiety, and ranged between 1.15 to 1.26 SDs above mean sample scores. Participants in the MDC profile showed moderate depression, mild stress, normal anxiety, and remained within sample mean levels. Finally, participants in the LDC scored in the normal range for depression, anxiety and stress, and steadily ranged 0.9 to 1.10 SDs below the sample mean. This indicates that participants in the HDC profile were at higher risk of experiencing distress symptoms compared to other latent profiles and expected normal population scores.

These findings are consistent with previous research which has demonstrated gamers do not encompass a homogenous group, but rather a group consisting of multiple different profiles identifiable by unique characteristics (Billieux et al., 2015; Colder Carras & Kardefelt-Winther, 2018; Faulkner et al., 2015; Lee et al., 2017; Lemmens et al., 2015; Pontes et al., 2014; Tullett-Prado et al., 2021; Ünübol et al., 2020). Interestingly, the presentation of such profiles suggest that most gamers (48.7%) represent a normative distribution of distress within the gaming population. This finding adds valuable evidence in support of the de-pathologizing of the gaming population, which has often been pathologized and is an ongoing topic of debate within the literature (O'Brien, 2018; Van Rooij et al., 2018). In other words, results support that being a gamer does not necessarily correspond with high/pathological levels of distress behaviours, such as depression anxiety and stress, examined in the present study.

Such findings are particularly relevant considering recent events wherein the Chinese government imposed further restrictions to minors' online video game play due to concerns surrounding gaming addiction (Goh, 2021). As of August 2021, the government restricted game time to a limit of one hour of play only on Friday, Saturday and Sunday, in addition to increasing the frequency and intensity of government inspections surrounding online gaming companies to ensure these restrictions are followed (Goh, 2021). Indeed, such policies are congruent with the idea that gaming is inherently negative, disregarding the role of gaming in normal development and how differences between gamers may relate to their unique experiences over time (Stavropoulos et al., 2021c).

4.2 Relationship between distress profiles and IGD levels

In line with previous research, the present study reported a significant association between one's IGD levels and their distress levels (Burleigh et al., 2018; Faulkner et al., 2015; Goeders, 2003; Lemmens et al., 2015; Liew et al., 2018; Wong et al., 2020). These findings are further supported when considering the aetiological models put forth to explain the underlying causes of IGD. For example, the self-medication (Griffiths, 2005; Griffiths et al., 2017) and Compensatory Internet Use (CIU) model (Kardefelt-Winther, 2014) propose that distressed individuals may engage in problematic gaming behaviour to cope with psychological suffering resulting in 'negative escapism' (Martín-Fernández et al., 2017; Valentino et al., 2010). Indeed, Lee et al. (2017) speculated that emotionally vulnerable individuals may engage in internet gaming for mood modification purposes that potentially stem from underlying depression or external stressors. Similarly, the Cognitive-Behavioural Theory of Pathological Internet Use (Davis, 2001) and the Person-Affect-Cognitive-

Execution (I-PACE) model (Brand et al., 2016) suggest that depression, anxiety, or stress can be contributing factors (either precipitating and/or perpetuating) regarding the development of IGD.

Considering the above, findings identified in the current study pose significant clinical practise directions. Specifically, observed distress profiles suggest that gamers with simultaneously higher levels of depression, anxiety, and stress may have a greater likelihood of developing IGD and thus, should be considered at risk and prioritized in prevention, intervention, and primary care. This implies that differential diagnosis processes (i.e., differentially assessing/ distinguishing symptoms of depression, anxiety, stress and disordered gaming) should be followed when assessing comorbid distress of those referred for problematic gaming behaviours to better describe one’s profile. Advancements in treatment for disordered gaming have been made, specifically with promising results in CBT-based psychotherapy (Li et al., 2020; Zajac et al., 2020). However, CBT-based psychotherapies targeting IGD often include exclusively cognitive techniques exclusively targeting depression (e.g., behavioural activation, or scheduling pleasurable non-gaming activities) or anxiety reduction techniques (e.g., systematic desensitization; Zajac et al., 2020). Therefore, programs and interventions designed for internet gaming disorder may benefit from including therapeutic techniques that target concurrently depression and anxiety.

4.4 Limitations and future research

It is important to note the current study presented a limited perspective regarding what encompasses distress. While it is true depression, anxiety, and stress have been postulated to possess a causal relationship with IGD (Griffiths, 2005; Griffiths et al., 2017; Kardefelt-Winther, 2014), the inclusion of only three broad indicators may fail to capture the scope of distress variability within the gaming population. Although not associated in a causal manner, incorporating symptoms positively associated with both distress and IGD (e.g., social withdrawal, fatigue, sleep disruption, Achab et al., 2011) may better describe the variety of distress experienced by the gamer and add more detail to potential risk profiles. Additionally, it must be emphasized that there is a lack of clear temporal association between psychiatric features and the onset of gaming disorder (Balhara et al., 2018). Therefore, further research is required to better understand a potential network of factors influencing risk factors such as depression, anxiety, or stress and the abuse of online applications, such as gaming (Kardefelt-Winther, 2014; Zarate et al., 2022). Furthermore, the lack of longitudinal data poses an issue for the validity of these profiles over time. In this context, is possible that the different distress profiles are constituting different stages of distress development for some individuals. Future research may wish to longitudinally profile gamers, using a broader range of distress symptoms or other factors thought to contribute to the development of IGD.

4.5 Conclusion

Findings, particularly those relating to IGD levels within distress profiles, have significant implications regarding the prevention, intervention, and assessment of IGD. Gamers presenting with higher levels of depression, anxiety, and stress should be considered as at greater risk of developing IGD. Thus, highlighting the need to target these individuals in primary care. Additionally, these findings call attention to the necessity of an efficacious treatment targeting depression, anxiety, and stress concurrently with IGD.

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Table 1. Sociodemographic information and descriptive statistics across gender groups.

	Gender		
Employment status	Female	Male	Other
Full-Time	86	238	7
Part-Time	49	61	1
Casual	11	12	0
Self-Employed	17	48	2
Retired	2	3	0
Unemployed	58	122	7
Full-Time Student	43	92	6
Other	49	46	8
Sexual Orientation			
Heterosexual/ Straight	211	529	3
Homosexual/ Gay	13	33	4
Bisexual	65	48	12
Unidentified/Other	26	12	12
Ethnicity / Background			
Black/ African-American	23	31	1
White/ Caucasian	193	380	22
Asian	59	124	1
Hispanic/ Latino	9	35	2
Aboriginal/ Torres Strait islander	1	0	0
Indigenous	1	1	1
Indian	1	4	0
Pacific Islander	1	3	0
Middle-Eastern	2	2	0
Mixed	25	40	3
Other	0	2	1
Romantic Relationship			
Yes	187	247	17
No	118	356	14
Prefer not to say	10	19	0
Education			
Elementary or Middle School	2	10	0
High School or Equivalent	74	166	11
Vocational/ TAFE	26	55	4
Some Tertiary Education	69	113	3
Bachelor's Degree (3 years)	76	137	5
Honours Degree or Equivalent (4 years)	35	69	5
Post graduate Degree (PhD, MS, etc.)	30	59	2
Other	3	13	1
Marital Status			
Single	164	405	23
Living with another	62	68	7
Married	68	120	0
Separated	2	4	0
Divorced	10	10	0
Widowed	2	1	0
Other	7	14	1
Descriptive statistics			
Depression	7.57 (5.80)	8.82 (5.98)	10.6 (6.58)
Anxiety	4.29 (4.16)	5.86 (4.79)	6.84 (5.37)
Stress	6.33 (4.66)	8.56 (4.90)	10.3 (5.58)
IGD	18.60 (7.26)	17.30 (6.72)	18.5 (7.53)

Table 2. Parameterization of variance-covariance structures, from the most to the least restrictive model.

Model	Variances	Covariances	Parameterization Type
1	Equal	Fixed to 0	Class-invariant diagonal parameterization model (CIDP). This model assumes that relationships across model indicators should not be estimated (covariances fixed at zero) and that different profiles will be qualitatively similar (equal variances)
2	Varying	Fixed to 0	Class-varying diagonal parameterization model (CVDP). This model assumes that relationships between model indicators should not be estimated (covariances fixed at zero), and that different profiles will be qualitatively different (varying variances).
3	Equal	Equal	Class-invariant unrestricted parametrization model (CIUP). Indicators are allowed to co-vary within profiles, and the variances and covariances are restricted to be equal across different profiles.
4	Varying	Varying	Class varying unrestricted parameterization (CVUP). All the indicators are allowed to co-vary within profiles, and the variances and covariances (i.e., residual correlations) are allowed to be different across profiles. In other words, this model assumes that there are relationships between model indicators within and between latent profiles that should be estimated (i.e., varying covariances), and that different profiles will be qualitatively different (varying variances).

Note = In this context, 'diagonal' indicates that the sum of elements in the variance-covariance matrix equals to zero, thus effectively preventing the model to estimate covariances between indicators.

Table 3. Initial model testing.

Model	Profiles	AIC	BIC	AWE	CLC	KIC
Class Invariant	1	8247.963	8277.215	8334.466	8237.963	8256.963
Diagonal	2	7120.837	7169.589	7266.682	7102.496	7133.837
Parameterization	3	6677.503	6745.757	6882.371	6651.142	6694.503
(CIDP)	4	6496.618	6584.372	6462.277	6517.618	6760.468
	5	6418.474	6525.729	6741.365	6376.093	6443.474
	6	6426.426	6553.182	6808.477	6375.887	6455.426
Class Variant	1	8247.963	8277.215	8334.466	8237.963	8256.963
Diagonal	2	6848.087	6911.465	7038.185	6823.744	6864.087
Parameterization	**3**	**6251.775**	**6349.280**	**6545.110**	**6213.450**	**6274.775**
(CVDP)	4	N.C	N.C	N.C	N.C	N.C
	5	N.C	N.C	N.C	N.C	N.C
	6	N.C	N.C	N.C	N.C	N.C
Class Invariant	1	6636.920	6680.797	6767.674	6620.920	6648.920
Unrestricted	2	6645.865	6709.243	6837.419	6620.067	6661.865
Parameterization	3	6467.436	6550.315	6716.675	6434.956	6487.436
(CIUP)	4	6415.292	6517.672	6723.420	6374.924	6439.292
	5	6270.024	6391.904	6637.278	6221.531	6298.024
	6	6278.008	6419.390	6704.482	6221.297	6310.008
Class Variant	1	6636.920	6680.797	6767.674	6620.920	6648.920
Unrestricted	**2**	**6167.752**	**6260.381**	**6446.322**	**6131.440**	**6189.752**
Parameterization	3	N.C	N.C	N.C	N.C	N.C
(CVUP)	4	N.C	N.C	N.C	N.C	N.C
	5	N.C	N.C	N.C	N.C	N.C
	6	N.C	N.C	N.C	N.C	N.C

Note: This table shows comparisons between different number of profiles for four possible combination of model parameters (including varying/fixed classes and varying/fixed covariances. Highlighted results (bold) indicate best model parameterization according to the best information criterion. Results showing N/C indicate that no convergence on a solution was possible.
AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; AWE = Approximate Weight of Evidence Criterion; CLC = Classification Likelihood Criterion

Table 4. Fit indices of CVDP with 3 profiles and CVUP with 2 profiles.

Model	Profiles	AIC	BIC	Entropy	Proportion of smallest profile	BLRT-p
CVDP	3	15671.03	15768.53	**0.84**	0.25	0.01
CVUP	2	**15605.49**	**15698.12**	0.74	0.34	0.01

Note: BLRT-p = Bootstrapped likelihood ration test. This table shows that CVDP model with 3 latent profiles demonstrate a higher entropy value resulting in better differentiation between profiles.

Table 5. Description of distress profiles including population share, and raw and Standardized mean scores of depression, anxiety, and stress.

Profile	N	%	Depression	Z Depression	Anxiety	Z Anxiety	Stress	Z Stress
High Comorbidity	251	25.9	14.90 (4.16)	1.15	10.30 (4.23)	1.22	13.40 (3.47)	1.26
Mid Comorbidity	471	48.7	7.76 (3.95)	-0.05	4.13 (2.44)	-0.17	6.70 (2.39)	-0.17
Low Comorbidity	246	25.4	1.77 (1.88)	-1.06	0.75 (0.91)	-0.92	1.76 (1.64)	-1.10

Note: Z scores represent standardizes scores and Standard deviation is presented between brackets.

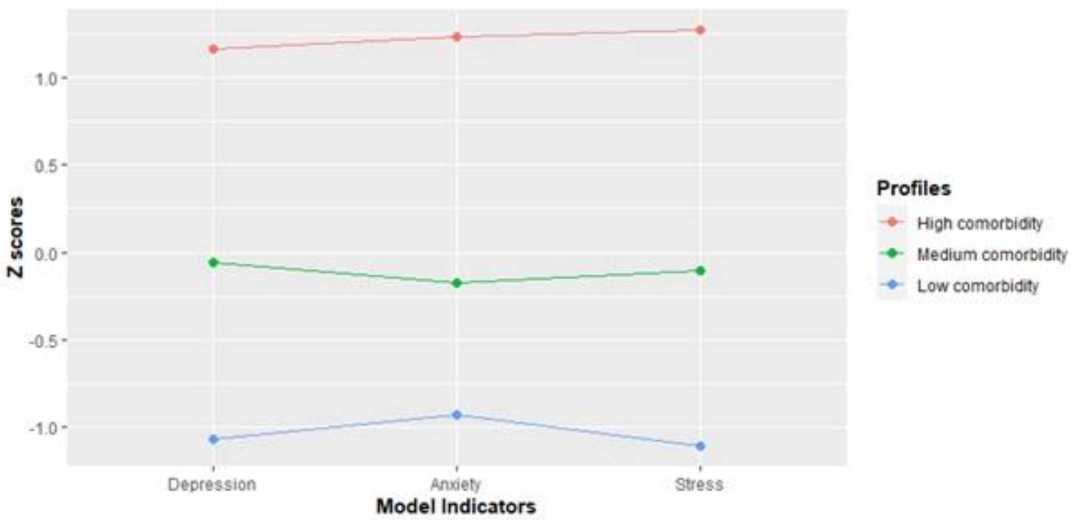

Figure 1. This plot illustrates three distinct latent profiles considering participant's symptoms of distress measured in standard deviation from the mean including depression, anxiety, and stress. The high line represents participants experiencing high levels of comorbid distress symptoms, the middle line medium levels, and lower line low levels.

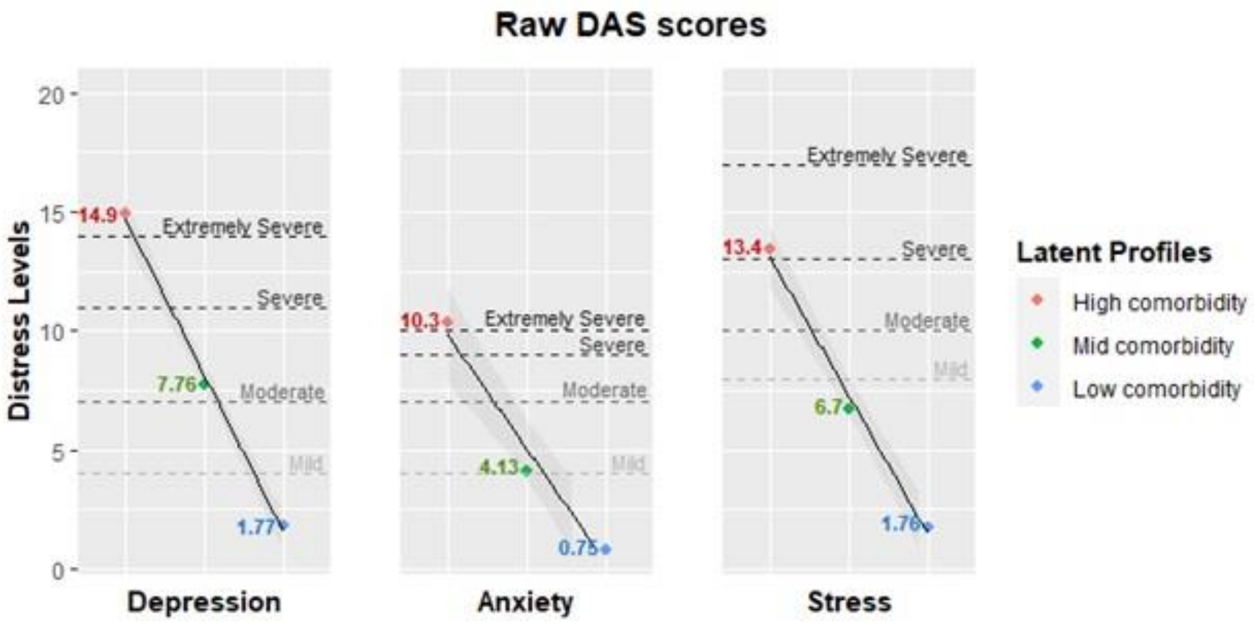

Figure 2. Here we see raw DAS scores discriminated by distress measure (i.e., depression, anxiety, stress) and latent profile. The horizontal dashed lines indicate cut off scores for mild, moderate, severe, and extremely severe distress scores. Depression scores are classified as normal (0-4), mild (5-6), moderate (7-10), severe (11-13), and extremely severe (14+); anxiety scores are classified as normal (0-3), mild (4-5), moderate (6-7), severe (8-9), and extremely severe (10+); stress scores are classified as normal (0-7), mild (8-9), moderate (10-12), severe (13-16), and extremely severe (17+). Finally, we joined the three latent profiles with a regression line to highlight differences across profiles.

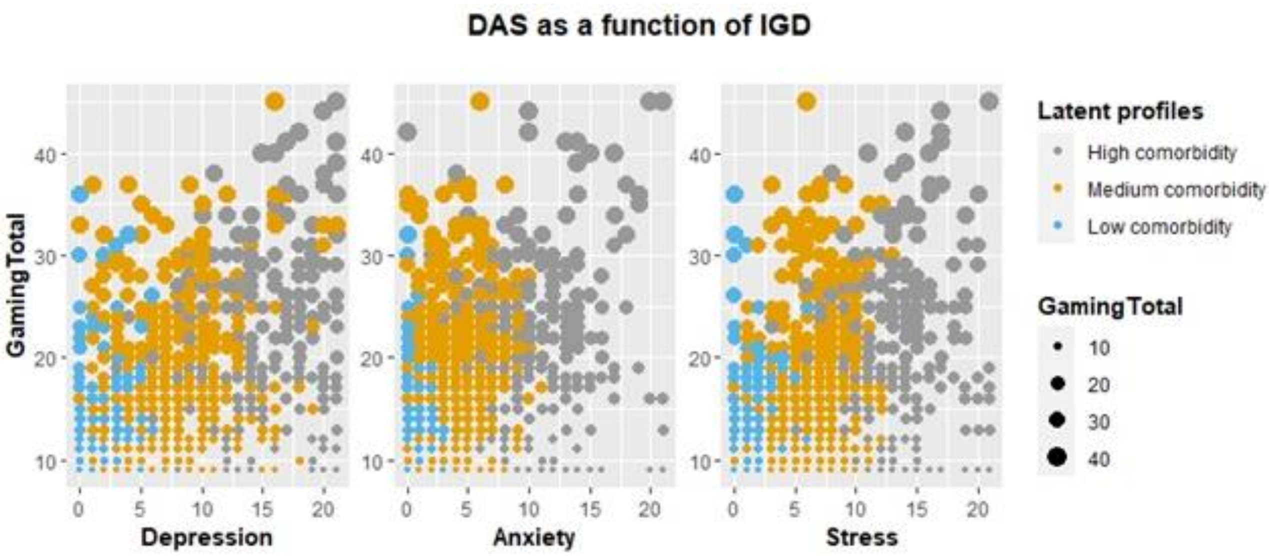

Figure 3. This plot shows relationships between IGD and distress symptoms (i.e., depression, anxiety, and stress) discriminated by distress profiles. As seen here, elevated levels of comorbid distress are associated with higher IGD scores.