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Mapping Mental Health Complexity in Esports: A Psychosocial Network Approach

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Abstract

Background

The rapid rise in popularity of esports has brought increased attention to the unique mental health challenges faced by esports players, yet research in this area remains in its infancy. Early research suggests a substantial mental health burden and has examined associations between esports-specific stressors, mental health and sleep disturbances. However, much of this work has relied traditional methodologies, providing limited insight into how affective, psychosocial, sleep-related, and esports-specific indicators are organised within this competitive performance environment.

Methods

To address this gap, we developed a bespoke 17-item questionnaire tailored for Directed Acyclic Graph (DAG) network analysis, providing a powerful methodological approach for mapping the conditional dependency structure of complex multivariate systems such as mental health.

Results

A total of 1025 esports players from over 60 countries completed the survey. Depressed mood emerged as a structurally prominent source node within the network, suggesting an organizing upstream role. Mental fatigue occupied an important position between affective variables and sleep/fatigue indicators. Additionally, its high prevalence and counterintuitive upstream position towards sleep indicators, suggests that it may warrant closer examination in future research on training load, recovery, and sleep in esports. Emotion control and a sense of autonomy formed a structural connection between upstream affective distress and downstream esports-specific indicators such as esports-related stress. Game-related thought preoccupation, a core feature of gaming disorder, emerged as a downstream sink node, consistent with the possibility that it represents a compound indicator of broader upstream psychosocial strain, rather than an organising feature itself.

Conclusions

Collectively, these findings provide an exploratory map of how mental health-relevant indicators were organised in this performance environment, and generate concrete, testable hypotheses for future longitudinal, experimental, and intervention research.

1. Introduction

Esports, involving the casual or organised activity of competitive video gaming, facilitated by in-game ranking systems or organised competitions (1), has grown at an extraordinary pace in recent years.

While solidifying itself as a prominent global phenomenon, an increasing number of amateur, semi-professional and professional players have entered a competitive performance environment (2). Esports, and gaming more broadly, has shown to have beneficial effects on, for example, cognitive flexibility and the social connectedness of players (e.g., 3, 4). However, it is also characterised by long, sedentary training schedules, an anti-social online climate, poor sleep, and high levels of performance pressure (e.g., 5). As the industry continues to grow, so too does the recognition of these performance-related demands and their potential influence on the emotional well-being, social functioning, and mental health of players (6, 7).

Recent evidence indicates a substantial burden of mental health problems and sleep disturbances among esports players (8, 9). Mental health is often conceptualised through two related but distinct dimensions: positive mental health (i.e., well-being) and mental ill-health (i.e., symptoms of mental disorders such as depression or anxiety) (10). Guided by this framework, and in line with a handful of smaller scale studies (11, 12), Kegelaers and colleagues (8) most recently found prevalence rates of 44.7% for depression, 33.4% for anxiety, 36.7% for poor well-being, and 69.3% for sleep disturbances in a large sample of 1105 esport players across different performance levels. Similarly, a systematic review by Akan and colleagues (13) reported both poor subjective and objective sleep levels in esports players, which in turn have been associated with decreased performance, diminished emotional regulation and increased risk of mental disorders (14). Consequently, recent research has sought to examine which esports-specific, emotional, social, and psychological stressors are embedded within broader patterns of player well-being and mental ill-health in competitive gaming contexts (6).

When discussing mental health, it is important to highlight its nature as a complex system rather than a single-cause phenomenon (15). Subsequently, understanding the aetiology of mental health problems in esports is challenging, as these problems are likely the result of complex, dynamic, and mutually reinforcing interactions among individual, social, environmental, and digital performance factors (16, 17). Several studies have suggested that esports players face a wide array of esports-specific stressors and health challenges (e.g., performance pressure, anti-social behaviour, intra-team conflicts, balancing life commitments, poor sleeping habits, long sedentary sessions), that may be associated with, or potentially compound, mental health problems (5, 18, 19). While encountering stressors is an inherent feature of competition, they are likely neither necessary nor sufficient for poor mental health (5, 20). Prior research has identified key psychosocial characteristics that may exacerbate, mediate, or modulate mental health outcomes among esports players. Esports players commonly report challenges in self-regulation and variable levels of social support (e.g., coaches, teammates, family), which in turn have been linked to lower levels of well-being and potential mental disorders (21, 22, 23). Furthermore, esports players report varying levels of basic psychological needs satisfaction and thwarting, including autonomy, relatedness, and competence, which have been linked to affect, well-being, and motivation in esports contexts (24, 25, 26). These issues may be further compounded by socio-emotional difficulties that have been associated with intensive or dysregulated gaming engagement, including emotion dysregulation, subjective feelings of loss of control in life, and an increase in interpersonal conflicts, which may add to the mental health burden experienced by some esports players. (27). Additionally,

research suggests that training and coaching structures, or the lack thereof, may contribute to player well-being (17). In grind-oriented environments with limited professional oversight, players may have fewer opportunities to develop adaptive self-regulation strategies and access consistent, high-quality support (28).

Although research has identified common stressors and demands within the esports environment, as well as distinct psychosocial vulnerabilities of esports players, comparatively little is known about how these factors are organised within competitive gaming as a digitally mediated performance environment (5, 6). One notable study examined the associations between esports-related stressors and mental ill-health outcomes (19), showing that stressors such as game uncertainty, personal worries, in-game pressure, and sleep quality significantly predicted burnout, anxiety, and depression. Complementing these regression findings, Poulus and colleagues (29) used undirected network analysis to show the structure of partial correlations among resilience factors, coping skills, and burnout symptoms within a sample of esports players. emphasising the complexity of, and interaction among, psychological factors. While these studies provide a valuable impetus in the domain of mental health research in esports, they do not address how different esports-related-stressors, sleep disturbances, socio-emotional factors, and mental health outcomes are organised as part of the broader mental health ecology.

Much of the existing literature follows an additive risk-factor logic, in which esport-related stressors, sleep problems, or psychosocial vulnerabilities are examined as separate predictors of mental health outcomes. While such work is highly valuable, the traditional methods of analysis used (i.e., prevalence estimates, correlations, standard regressions, and partial correlations) possess inherent limitations. They provide limited insight into whether esports-specific concerns are structurally positioned as organising features of distress, as downstream correlates of broader psychological strain, or as bridging components connecting affective, regulatory, and/or sleep-related processes. To better address these limitations and more adequately capture the structural complexity of mental health within an environment, network approaches such as Bayesian Gaussian Graphical Copula Models (BGGCMs) and Directed Acyclic Graphs (DAGs) should be considered (30, 31).

Together, these advanced statistical models provide a powerful exploratory approach for mapping complex multivariate systems by elucidating patterns of model-derived directed conditional dependency pathways between variables (32). BGGCMs allow for the estimation of partial correlations between variables while controlling for all others in the network. It offers a nuanced understanding of the structure of mental health symptoms, esports-specific stressors, and other included variables by highlighting which associations remain once shared variance with all other variables is controlled for. DAGs extend this approach by introducing directionality to these relationships, identifying plausible conditionally dependent pathways between variables. Such network approaches offer a promising avenue to generate a constrained set of candidate pathways that can guide future longitudinal, experimental, and intervention-focused research.

The current study applies these network approaches in a primarily exploratory, hypothesis-generating manner (33) to provide insight into the complex, interconnected structure among esports-specific stressors, psychosocial factors (basic psychological needs, social support, emotion regulation), sleep factors, psychosomatic symptoms, and mental ill-health symptoms. Specifically, we aim to elucidate the conditional dependency structure among these variables, generate tentative hypotheses about how they may be organised within the broader psychosocial and digital performance context of esports, and identify candidate nodes and pathways for future confirmatory, longitudinal, and intervention-focused research. To our knowledge, this is the first study in esports to apply these combined network models, moving beyond bivariate analyses, traditional regressions, and undirected network analyses to provide a more detailed exploratory map of mental health relevant processes in esports.

2. Methods

2.1 General Analysis Routine

The Methods and Results sections follow the reporting standards for psychological network analyses in cross-sectional data as set out by Burger and colleagues (34).

Sample and Data Collection. For this analysis, we included the data collected through a large international cross-sectional online survey. This research was part of *blinded for review purposes*, which aimed to better understand the current state of player well-being and mental health outcomes in esports *blinded for review purposes* and investigate complex interactions between esports-specific demands, psychosocial factors, and mental health outcomes. This project was a collaborative effort of industry partners and research institutions from *blinded for review purposes*. The survey was disseminated through different social media channels of the project partners, as well as through external partnerships with YouTube and Twitch TV channels, with the YouTube partnership being paid. Potential participants could access the online survey through a hyperlink or QR code. No incentives were offered to the participants. Ethical approval was granted by *blinded for review purposes* before distributing the survey. Data collection ran from October 2024 until February 2025, resulting in a sample of 1025 esports players.

Survey Design/Variable Selection Procedure. Although validated, multi-item questionnaires are indispensable for latent variable modelling, their direct use as nodes in psychological network models can be methodologically problematic (34). Within traditional reflective scales, items are constructed as partially interchangeable indicators of a common latent construct (e.g., sleep quality, anxiety, depression), reflecting shared variance rather than direct associations between distinct psychological components. This violates a core assumption of network modelling, namely that nodes should represent autonomous elements of a system whose connections are substantively interpretable (15, 34). Consequently, overlapping or redundant items can artificially inflate edge weights and centrality estimates, distorting the network topology and undermining interpretability, emphasising the need for each node to be theoretically justified as a meaningful component of the modelled system. As such,

items should be selected and/or constructed to reflect distinct, potentially interacting mental health-relevant symptoms and esports challenges, rather than reflective indicators of other latent constructs (30, 35, 36).

To this end, we developed a bespoke questionnaire with theoretically grounded single-item indicators driven by both conceptual and analytic considerations: by anchoring each node to a distinct, well-defined construct, we minimised redundancy-induced network structure, preserved the interpretability of individual nodes, and reduced respondent burden without sacrificing construct coverage. Items were identified through literature review and multiple iterative discussions within the project consortium comprising clinical-, sport-, and developmental psychologists, a somnologist, and psychometrician as part of *blinded for review purposes*, with additional feedback from esports stakeholders (e.g., (e)sports psychologists and other domain experts) and statistical experts with specific expertise in advanced network analysis. Items were selected based on conceptual specificity and, through iterative review, assessed for face validity in relation to the relevant hypothetical construct and the applied context. Crucially, the psychometric requirements of network analysis differ fundamentally from those of scale construction within a Classical Test Theory framework (35). Accordingly, avoiding conventional validated multi-item scales is an analytic necessity for the estimation of a symptom-level network of potentially interacting components, with minimised topological overlap and redundancy. Where possible and appropriate, items were adopted and adapted from existing questionnaires.

As symptoms of anxiety, depression, and sleep disturbance are highly prevalent in esports (8), distinct items assessing their core characteristics were included. Depressed mood and anhedonia were adopted from the PHQ-2, and anxiety and uncontrollable worrying from the GAD-2 (37, 38), reflecting core symptoms of depression and anxiety according to the DSM-5 criteria. Sleep quantity and sleep quality items were inspired by components of the Pittsburgh Sleep Quality Index (39). Given the demanding training schedules and prolonged cognitive load associated with esports participation (18, 22, 40, 41), we included indicators of mental fatigue, physical fatigue, and somatic symptoms (e.g., pain, weakness, numbness). Beyond symptom indicators, we also included esports-related psychological factors that have been linked to a potential strain on mental health in gaming and esports contexts, including esports-related stress (42), gaming-related thought preoccupation (27), and difficulties with emotion regulation under pressure (22, 23). Additionally, as a lack of social resources are often highlighted as a potential risk factor for poor mental health in performance environments (22, 23), indicators assessing perceived insufficiency of support both the personal and esports environment were also included. Finally, drawing on self-determination theory (26) and the work of Hong and colleagues (25), we included indicators of basic psychological needs thwarting (autonomy, competence, and relatedness), as a conceptually relevant framework for understanding players' experiences in performance contexts.

This resulted in a final 17-item questionnaire (see Table 1). All items used 10-point Likert-type response scales (1 - *almost never*; 10 - *constantly*) to ensure sufficient variability (34). A common reference period of the past two weeks was used to support consistent interpretation across variables and to minimise measurement-related artifacts that could bias network estimation and edge interpretation.

Table 1
Questionnaire items

Construct	Question	Item label
Depressed mood	How often have you felt down, depressed or hopeless?	“DepressedMood”
Anhedonia	How often have you had little interest or pleasure in doing things?	“Anhedonia”
Anxious mood	How often have you felt nervous, anxious or on edge?	“Anxiety”
Excessive worrying	How often have you not been able to stop or control worrying?	“Worrying”
Quality of sleep	How often did you feel you did not sleep *well* enough?	“SleepQuality”
Sleep duration	How often did you feel you did not sleep *long* enough?	“SleepQuantity”
Mental fatigue	How often have you felt mentally fatigued?	“MentalFatigue”
Physical fatigue	How often have you felt physically fatigued?	“PhysicalFatigue”
Somatic symptoms	How often have you experienced any pain, weakness, numbness, tingling or any other physical symptoms?	“Pain”
Esports-related stress	How often have you felt stressed because of your esport?	“EsportsStress”
Gaming-related thought preoccupation	How often have there been periods when all you could think about was the moment that you could play video games?	“GamePreoccupation”
Emotion regulation difficulties under pressure	How often have you experienced difficulties controlling your emotions when under pressure?	“LackEmotionControl”
Lack of perceived support in the personal environment	How often have you felt insufficiently supported by people in your personal environment (e.g., parents, partner, friends, etc.)?	“LackSupportPers”
Lack of perceived support in the esports environment	How often have you felt insufficiently supported by people in your esports environment (e.g., coaches, teammates, etc)?	“LackSupportEsport”
Basic psychological needs thwarting autonomy	How often have you experienced a lack of freedom to make your own decisions in your esport?	“LackAutonomy”
Basic psychological needs thwarting competence	How often have you felt that you were not really skilled in your esport?	“LackSkill”

Construct	Question	Item label
Basic psychological needs thwarting relatedness	How often have you felt you had no real close relationships with other people in your esport?	“LackConnection”

Estimation Methods. An initial Bayesian Gaussian Graphical Copula Model (BGGCM) was estimated to identify key partial correlational relationships among variables and assess the robustness of edge inclusion. BGGCMs were chosen as they provide “a principled alternative to various penalised approaches” (43, p. 2) such as traditional Gaussian Graphical Models, while performing equally well as other estimation methods. They account for ordinal and non-Gaussian data by modelling dependencies via a copula, thus avoiding Gaussian assumptions (43). The estimations of the BGGCM network were conducted using the Birth-Death Markov Chain Monte Carlo (BDMCMC) algorithm in the *bdgraph* function of the *BDgraph* package in R (44).

Second, a Directed Acyclic Graph (DAG) was estimated using the greedy search Hill Climbing algorithm in the *bnlearn* package in R (45). DAGs extend the undirected approach of BGGCMs by introducing directionality and conditionally dependent pathways between the variables. In line with existing theoretical and applied research, the ordinal Likert scale data of this study has been treated as continuous as to avoid information loss (e.g., 46).

Accuracy and Stability of Edge-Estimates. To assess the accuracy of the edge weight estimates in the BGGCM, 100.000 iterations of the estimation were run with a burn-in time of 50.000 (43). The convergence trace plot was visually inspected to judge chain stability. Comparisons between different *g.prior* values were made, to select a data-driven Bernoulli Prior Probability which best fit the data. The value was eventually set at 0.1 to ensure a sparse and interpretable network. A *p_link* (i.e., posterior edge inclusion probability) threshold was set at 0.85 and the resulting Maximum A Posteriori probabilities were used to further ensure a sparse and confident network. Finally, multiple chains were run on different seeds and compared to each other using the Hamming distance and Jaccard index to ensure stability across different estimations.

To assess accuracy of the edge estimates of the DAG, we conducted the *boot.strength* routine implemented in the *bnlearn* package (45), using non-parametric bootstrapping with 5000 bootstrap samples with the greedy search Hill Climbing algorithm, with 5 restarts and a *perturb* value of 10 to not remain stuck in local optima (47). Next, we calculated the average network with the *averaged.network* function of the *bnlearn* package. In line with guidelines and previous empirical papers, we removed the weak edges by adopting a strength threshold value of 0.85 (i.e., edges that appeared in more than 85% of networks were included), and a direction value of at least 0.5 (i.e., the proportion of bootstrapped networks wherein the edge pointed from node A to node B is larger than 50%), leaving us with solely the most robust edges (31). Finally, we used the *arc.strength* function of the *bnlearn* package to calculate the strengths of all edges in the network, utilising their Bayesian Information Criterion (i.e., a relative measure of a model’s goodness-of-fit; *BIC-g*) criterion. Additionally, we compared the Bayesian

Information Criterion of the estimated network with an empty network to ensure confident network selection (48).

Statistical Packages. The analyses have been conducted using R (version 4.4.3; 49). For the network estimation of the BGGCM, the *bdgraph* function in the *BDgraph* package was used (44). For the DAG network estimation, the *boot.strength* function in the *bnlearn* package was used (45). The centrality measures for both models were calculated using the *strength, degree, betweenness*, and *eigenvector* functions of the *igraph* package, and the *arc.strength* function of the *bnlearn* package for the DAG (45, 50). Additionally, the *estimateNetwork* function of the *bootnet* package was used for estimating predictability through a Relative Importance Network (51). Finally, all networks have been visualised using the *qgraph* package (52).

2.2 Analysis-Specific Routine

Centrality Indices. We estimated node-level centrality indices of the BGGCM using the posterior mean adjacency matrix (*selected_g*), posterior edge inclusion probabilities (*p_link*) and the estimated precision matrix (*K_hat*) derived from the *BDgraph* function with the posterior edge inclusion probabilities thresholded at 0.85. Centrality metrics included partial correlations (i.e., partial correlations/conditional dependencies of edges between nodes), expected influence (i.e., sum of node-level partial correlations), degree (i.e., number of connections of a node), betweenness (i.e., frequency with which a node lies on shortest paths between others), and eigenvector (i.e., connection to other well-connected nodes).

To quantify how well a node is connected to other nodes in the DAG structure, we investigated arc strength (i.e., the change in model score when arc is removed, based on their *BIC-g* score), betweenness (i.e., frequency with which a node lies on shortest paths between others), in expected influence (i.e., sum of incoming edge weights to a node) and out expected influence (i.e., sum of outgoing edge weights from a node) as centrality measures. Lastly, the DAG was visually inspected for potential minimal edge cuts (i.e., cases in which removing one or two nodes eliminated directed connectivity between parts of the estimated graph, e.g., 53).

Finally, we calculated node predictability by means of a Relative Importance Network (RIN). Lindeman-Merenda-Gold (*lmg*) values were calculated, representing the proportion of explained variance attributed to each predictor after accounting for all the other nodes in the network (51).

3. Results

3.1 General Analysis Routine

Final Sample Size. A total of 1105 participants were initially recruited *blinded for review purposes*. For the current analysis, only respondents who fully completed the distinct questionnaire used in this study were retained. Applying listwise deletion for incomplete cases resulted in a final sample of 1025 participants. Participants had a mean age of 27.74 (SD = 7.37) and were required to be at least 18 years

old. The sample comprised 845 participants who identified as man (82.4%), 139 who identified as woman (13.6%), 29 who defined their gender in another way (2.8%), and 12 who preferred not to share their gender identity (1.2%). Reported performance levels ranged from *recreational* (*"*Occasionally competing online or at the lowest-tier local events"; *n* = 288), *foundational* (*"*Regularly competing in lower-tier online competitions, local LAN events, events at the bottom of the regional ladder"; *n* = 292), *pre-elite* ("Competing in second-tier or regional in-person competitions or online competitions, competing for top-level in-game rankings"; *n* = 232), *elite* (*"*Competing in prestigious tournaments with a good number of top-tier teams, slightly below the highest-level international competitions"; *n* = 144), and *mastery* level ("Competing in internationally top ranked tournaments, organised by well-established franchises"; *n* = 69) (see Supplementary Table S1 for descriptive statistics and Supplementary Table S2 for zero-order correlations between variables).

Results of the Accuracy and Stability Checks. In estimating the BGGCM, edge probabilities showed strong fluctuations in the initial 5000 bootstrap iterations, but soon stabilised after 10.000 iterations, showing signs of high confidence and convergence (Fig. 1). The calculation of the average normalised Hamming distance and average Jaccard index resulted in excellent respective scores of 0.0098 and 0.9637. Finally, a Posterior Probability (*p_link*) threshold of .85 was set (Briganti et al., 2022), resulting in an average absolute edge probability score of 0.9821.

BGGCM Posterior Probabilities convergence plot of all possible links

Description

Convergence plot from the BDgraph plotcoda function. Each line represents the cumulative occupancy fraction (posterior inclusion probability) of a possible edge in the graph across BDMCMC iterations.

With regards to the DAG estimation, the Hill Climbing algorithm was ran for 5000 bootstrap samples, with five restarts and a perturb value of 10. Respective strength and direction thresholds of 0.85 and 0.5 were set to ensure robust and stable edges. The difference between the model score (i.e., BIC-g) and the score of an empty network was 3691.34, indicating very strong confidence in model selection (48).

3.2 Analysis-Specific Routine

Predictability. To calculate the predictability of the variables (i.e., proportion of explained variance attributed to each predictor), a Relative Importance Network (RIN) was estimated (see Figure S1). Normalised *lmg* values (i.e., normalised contributions to total R^2 of a node) ranged from 0 to 0.45 ("SleepQuality" to "SleepQuantity"), with a mean normalised *lmg* value of 0.06. The five highest scoring variables based on *RawOutStrength* (i.e., sum of the weights of outgoing edges based on non-normalised lmg/R^2 contributions) were "DepressedMood" (0.69), "Anxiety" (0.62), "PhysicalFatigue" (0.60), "SleepQuality" (0.58) and "MentalFatigue" (0.57) (see Table S3). Additionally, node-level *Adjusted* R^2 values (i.e., proportion of variance in a node explained by its DAG-structure parents) were calculated (see Table S4).

Network Visualisation. The BGGCM network visualisation is presented in Fig. 2 and Figure S2. Here, edges represent partial correlations between the copula transformed items. Edge strength (i.e., partial correlation) scores ranged from 0.0735 (“Anxiety” – “SleepQuality”) to 0.4846 (“SleepQuantity” – “SleepQuality”) (see Table S5).

Figure 2

Bayesian Gaussian Graphical Copula Model of the bespoke questionnaire data (edge width based on partial correlations and node size based on mean score)

Description

Bayesian Gaussian Graphical Copula Model (BGGCM) network visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each edge depicts an estimated partial correlation between two nodes, controlling for all other variables in the model; edge presence and thickness reflect the strength of these conditional associations.

The DAG network visualisations are presented in Fig. 3 and Supplementary Figures S3-S4. In all visualisations, edges that are present in the graph are included because their strength is greater than .85 and their direction is greater than .50, and represent conditional dependencies between variables (i.e., the parent node X could be present without its child node Y, but the presence of the child node Y implies the presence of X; 54). It is important to note that the edge direction in the DAG model is model-derived, reflecting statistical conditional dependence rather than definitive evidence of causality or temporal ordering (54). Moreover, because DAGs impose an acyclic structure, other plausible mechanisms, such as reciprocal or feedback processes, cannot be represented and therefore remain viable alternative interpretations. Edge thickness in Fig. 3 is based on the change in the global Bayesian Information Criterion when that edge is removed from the network (i.e., the more the edge contributes to the overall model fit, the thicker it is), while edge thickness in supplementary Figure S4 represents directional probabilities (i.e., the proportion of bootstrapped networks wherein the edge pointed from node A to node B). Edge weight (*BIC-g* i.e., relative goodness-of-fit measure where more negative values indicate a greater loss in model fit) scores ranged from − 11.25695 (from “LackSupportEsports” to “LackConnection”) to -286.12224 (from “DepressedMood” to “Anxiety”) (see Table S6). Directional probabilities ranged from .5172 (from “LackConnection” to “LackSkill”) to .9727 (from “MentalFatigue” to “LackSkill”) (see Table S7).

To facilitate interpretability of, and consistency between, the BGGCM and DAG visualisation, custom layouts were employed.

Figure 3

Directed Acyclic Graph of the bespoke questionnaire data – based on BIC-g scores

Description

Directed acyclic graph (DAG) network visualisation. Each node represents a questionnaire item and its size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child in the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations.

Network Density and Average Absolute Edge Weights. To ensure a sparse and interpretable network, a posterior edge inclusion probability (*p_link*) threshold of .85 was set in the BGGCM estimations. Based on both the posterior edge inclusion probabilities and Maximum A Posteriori probabilities, this resulted in a total of 34 edges adopted network (25% of 136 total possible edges) with an average absolute edge weight of 0.1908 based on their partial correlations. This percentage of selected edges falls within the ideal boundaries which existing literature describes as an optimal range for psychological data modelling (Quinn et al., 2016).

An edge strength (*arc.strength*) threshold of .85 (i.e., present in at least 85% of bootstrap samples) was adopted in the DAG estimation. This resulted in a total of 31 directed edges in the symptom frequency DAG (22.79% of 136 total possible edges), with an average edge weight of -76.618 based on their Bayesian Information Criterion (*BIC-g*) scores.

Centrality Indices. Supplementary Tables S8-S11 present the results of the centrality analyses of the BGGCM (expected influence, degree, betweenness, and eigenvector). The three most influential nodes based on *Expected Influence* (i.e., sum of absolute node-level partial correlations) were “DepressedMood,” “LackAutonomy” and “Anxiety.” In contrast, the three least influential nodes were “GamePreoccupation,” “LackSkill” and “Pain.” The nodes with the highest *Betweenness* scores (i.e., frequency with which a node lies on shortest paths between others) in the BGGCM were “LackAutonomy,” “LackEmotionControl,” and “Worrying.” In contrast, the nodes with the lowest *Betweenness* scores were “GamePreoccupation,” “SleepQuantity,” and “LackSupportEsport.”

Supplementary Tables S12-S14 present the results of the centrality analyses of the DAG (Betweenness, InExpectedInfluence and OutExpectedInfluence). “DepressedMood” emerged as the sole source node of the network (zero *InExpectedInfluence*), whereas “Anhedonia,” “GamePreoccupation,” “LackSkill,” “LackSupportPersonal,” “SleepQuality” and “Worrying” emerged as sink nodes (zero *OutExpectedInfluence*). Furthermore, “DepressedMood” (-812.65), “LackAutonomy” (-341.86) and “MentalFatigue” (-300.48) showed the highest *OutExpectedInfluence* scores, while “Anxiety” (-286.12), “Anhedonia” (-261.48) and “PhysicalFatigue” (-242.47) showed the highest *InExpectedInfluence*. Additionally, “LackAutonomy,” LackEmotionControl,” and “LackSupportEsports” showed the highest *Betweenness* scores (i.e., frequency with which a node lies on shortest paths between others). It is important to note that Betweenness and other centrality values should be interpreted cautiously, as their stability and applicability in psychological networks remains debated (54).

To identify structural bottlenecks in the DAG network, a single-node and two-node cut (or s-t articulation point) analysis was conducted (53). When these nodes are removed, they interrupt directed reachability

within the estimated graph, fully disconnecting one part of the network from another. This analysis showed that “LackEmotionControl” and “LackAutonomy” together formed a minimal edge cut (i.e., removing both nodes eliminated all directed paths from “DepressedMood” and “Anxiety” to “EsportsStress,” “GamePreoccupation” and “LackSupportEsport”). Additionally, the analysis showed that both “MentalFatigue” (eliminating all directed paths from “DepressedMood” and “Anxiety” to “SleepQuantity” and “PhysicalFatigue”), and “DepressedMood” (disconnecting “Anhedonia” from the network if removed) functioned as single minimal edge cut.

Specific Nodes and Edges. The five variables with the highest average score were “LackSkill” (5.68), “MentalFatigue” (5.53), “SleepQuantity” (5.52), “SleepQuality” (5.4) and “Anhedonia” (4.98). In contrast, the five variables with the lowest average score were “LackAutonomy” (3.6), “LackSupportEsport” (3.61), “Pain” (3.67), “EsportsStress” (3.82) and “LackSupportPersonal” (4.24).

As mentioned, it remains important to emphasise that the directionality of the DAG is model-informed and alternative interpretations, such as reciprocal processes, remain plausible. As we analysed the roles of different nodes in the DAG network, we see that “DepressedMood” appeared as a source node in the estimated graph (*InExpectedInfluence* = 0.00), with only outgoing and no incoming edges. Conversely, the nodes “Anhedonia,” “GamePreoccupation,” “LackSkill,” “LackSupportPersonal,” “SleepQuality” and “Worrying” functioned as sink nodes (*OutExpectedInfluence* = 0.00), with only incoming and no outgoing edges.

Based on their BIC-g score (*arc.strength*), the five strongest edges within the DAG model were those from “DepressedMood” to “Anxiety” (-286.12), from “DepressedMood” to “Anhedonia” (-261.48), from “MentalFatigue” to “PhysicalFatigue” (-242.47), from “LackAutonomy” to “EsportsStress” (-178.70), and from “SleepQuantity” to “SleepQuality” (-168.16). These edges represent the best-supported conditional dependencies within the network, with their BIC-g scores indicating the extent to which the model fit deteriorates when the respective edge is removed. In contrast, the five weakest edges were those from “LackSupportEsports” to “LackConnection” (-11.26), from “LackEmotionControl” to “LackSkill” (-14.40), from “Anxiety” to “SleepQuality” (-16.27), from “EsportsStress” to “GamePreoccupation” (-21.25815), and from “Pain” to “LackConnection” (-22.23). While these edges have the weakest BIC-g scores, they are nevertheless present in 85% of the bootstrapped estimations (i.e., although they contribute relatively little to the overall model fit, their presence is consistently supported across resamples).

Visual inspection of the DAG revealed three thematically coherent subnetworks: a psychopathological cluster, a somnological fatigue cluster and an esports-specific cluster. Although these subnetworks remain part of the larger interconnected model, identifying them provides a useful lens for understanding domain-specific processes within the broader network.

The psychopathological subnetwork (Fig. 4) contains the four variables taken from the PHQ2 and GAD2 questionnaires (“DepressedMood”, “Anhedonia”, “Anxiety” and “Worrying” [37, 38]) alongside “MentalFatigue”, “LackEmotionControl” and “LackSupportPersonal”. “DepressedMood” appeared as a source node, with strong directed edges to “Anhedonia” (BIC-g = -261.48, dir = .86) and “Anxiety” (BIC-g =

-286.12, dir = .55) (i.e., the two best-supported conditional dependencies of the entire network) and moderate directed edges to “Worrying” (BIC-g = -63.83, dir = .66), “MentalFatigue” (BIC-g = -85.18, dir = .58), “LackEmotionControl” (BIC-g = -37.16, dir = .81) and “LackSupportPersonal” (BIC-g = -78.88, dir = .90).

Figure 4

Psychopathological subnetwork – edge thickness based on BIC-g score

Description

Psychopathological subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations. This psychopathological subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

The somnological subnetwork (see Fig. 5) shows the interplay between the sleep quality and quantity variables, physical and mental fatigue variables, perceived lack of skill and affective depression and anxiety variables. The variable “DepressedMood” remained positioned as a source node, with outgoing edges to “MentalFatigue” (BIC-g = -85.18, dir = .58) and “Anxiety” (BIC-g = -286.12, dir = .55), and through them, indirectly connecting to “SleepQuantity” (from “MentalFatigue”: BIC-g = -29.08, dir = .65), “SleepQuality” (from “Anxiety”: BIC-g = -16.27, dir = .67), “PhysicalFatigue” (from “MentalFatigue”: BIC-G = -242.47, dir = .61), and “LackSkill” (from “MentalFatigue”: BIC-g = -28.94, dir = .97). While the edge from “MentalFatigue” to “LackSkill” was relatively weak (BIC-g = -28.94), it had the highest direction of all edges present in the network (dir = .97). Additionally, “SleepQuality” functioned as a structural sink node in the network (*OutExpectedInfluence* = 0.00, *InExpectedInfluence* = -223.85) and received a strong edge from “SleepQuantity” (BIC-g = -168.16, dir = .64), a moderate edge from “PhysicalFatigue” (BIC-g = -71.96, dir = .71) and a weak edge from “Anxiety” (BIC-g = -16.27, dir = .67). As mentioned before, the mean scores of “SleepQuality” (5.4), “SleepQuantity” (5.52) and “MentalFatigue” (5.53) were among the highest of the network, marking them as salient problems.

Figure 5

Somnological subnetwork – edge thickness based on BIC-g score

Description

Somnological subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped

DAG estimations. This somnological subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

The final thematic cluster is the esports-specific subnetwork (see Fig. 6). Within this cluster, “DepressedMood” again appeared as a source-positioned variable in the estimated DAG, with directed edges to “Anxiety” (BIC-g = -286.12, dir = .55), “LackEmotionControl” (BIC-g = -37.16, dir = .81), “LackSupportPersonal” (BIC-g = -78.88, dir = .90) and “MentalFatigue” (BIC-g = -85.18, dir. = .58). “GamePreoccupation” functioned as a structural sink node in the estimated graph (*OutExpectedInfluence* = 0.00, *InExpectedInfluence* = -52.97). In addition, both “LackEmotionControl” (*Betweenness* = 0.044) and “LackAutonomy” (*Betweenness* = 0.056) emerged as potential structural bottleneck nodes (i.e., two highest betweenness scores of the entire network). As mentioned, “LackEmotionControl” and “LackAutonomy” together formed a minimal edge cut (i.e., removing both nodes eliminated all directed paths from “DepressedMood” and “Anxiety” to “EsportsStress,” “GamePreoccupation” and “LackSupportEsports”), marking them as a candidate structural bottleneck within the current estimated network.

Figure 6

Esports-specific subnetwork – edge thickness based on BIC-g score

Description

Esports-specific subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations. This esports-specific subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

4. Discussion

As esports has risen in popularity and scale, so too have concerns about the mental health status of players within this competitive gaming environment. With players reporting high levels of mental ill-health outcomes (e.g., depression, anxiety, and sleep disturbances), researchers have questioned which esports-specific factors create a context that may be implicated in these outcomes (e.g., 6, 8, 19). To this end, the aim of this study was to explore the complex interactions between esports-related-stressors, sleep disturbances, socio-emotional factors, and mental health outcomes. We therefore estimated two complementary network models (i.e., BGGCM and DAG), using them in an explicitly exploratory, hypothesis-generating manner (33). Taken together, these models provide a structured description of conditional dependencies among the included variables and generate tentative hypotheses regarding how these indicators may cluster and relate within a broader competitive gaming ecology (15, 32, 54).

It is important to note that the directionality of the DAG is model-informed and based on statistical conditional dependence (i.e., the parent node X could be present without its child node Y, but the presence of the child node Y implies the presence of X), rather than true causal relationship or temporal antecedence (54). Accordingly, the present results should be read as an exploratory between-person description of how the selected indicators were organised in this sample, and as a basis for more focused follow-up research.

Our network positioned depressed mood in a notable upstream position within the estimated DAG. In the present model, a depressed mood emerged as the sole source node, sending conditional dependency edges to other variables without receiving any incoming edges. This does not demonstrate that depressed mood temporally or causally initiates the rest of the system. It does, however, indicate that depressed mood occupied a structurally prominent position in the current model, and tended to co-occur with a wide range of downstream indicators. Additionally, depressed mood had the highest out-strength in the RIN network, again suggesting a strong, structurally prominent role. Together, these findings suggest that a depressed mood may represent an important organising feature of the present network. This interpretation is broadly consistent with research in traditional sports showing that depressive symptoms are associated with impaired functioning, injury risk, and burnout in elite athletes (56), suggesting that low mood may play a structurally similar role across performance domains. Furthermore, this depressed mood emerged as the most upstream node for all three thematic subnetworks (psychopathological, somnological and esports-specific) and showed associations to anhedonia, anxiety, a lack of emotion control, worrying, mental fatigue and a lack of perceived social support in the personal environment. Notably, the strongest connections in the network involved its edges to anxiety and anhedonia, reflecting the well-known co-occurrence of these mental ill-health symptoms in general, traditional sports, and esports (8, 57, 58).

A lack of emotion control and a lack of autonomy emerged as important connecting nodes in the current network structure. This suggests that these variables may represent important points of convergence through which pathways between core psychopathological symptoms and esports-specific outcomes are organised. Although this does not establish causal mediation, it provides a useful indication of where psychological distress and esports-specific difficulties appear to connect within the current network. This interpretation aligns with Self-Determination Theory, where autonomy is viewed as central to well-being (59), and with prior findings linking psychological need thwarting to burnout and potential mental health issues in esports (24, 25). Similarly, difficulties in emotion regulation are also known challenges in esports (21, 22, 23), and our findings suggest that these difficulties may be linked to different downstream esports-specific outcomes. Recent syntheses of esports psychology, early intervention work, and diary research likewise highlight the importance of stress, coping, and emotion regulation in the well-being of players (17, 60, 61). In positioning autonomy and emotion control as potential connecting points between distress and esports-specific outcomes (such as esports stress and game-related thought preoccupation), the present findings extend this emerging literature and generate more specific hypotheses for longitudinal and intervention research.

As mentioned, our network revealed a distinct esports-specific cluster following the emotion control and autonomy variables. Within the current model, game-related thought preoccupation emerged as a sink node, with only incoming and no outgoing edges. This pattern opens avenues for future research, including the possibility that game-related thought preoccupation may, in some players, be a compound indicator of broader upstream psychosocial strain, rather than an organising feature itself. This interpretation is consistent with research by Bányai and colleagues (62, 63), who found that psychiatric distress was associated with gaming disorder symptoms partly through escapism and coping-related mechanisms. Taken together with this literature, our findings suggest that dysregulated game-related thought preoccupation may, for some players, reflect a maladaptive coping response to mental health difficulties, rather than simply reflecting high gaming engagement. A similar interpretation has been proposed in traditional sports, where compulsive exercise or overtraining have been conceptualised as maladaptive responses to stress and dysregulated affect, rather than the primary causes of psychopathology (e.g., 64, 65).

The somnological subnetwork in our model, highlights the pervasive sleep-related issues faced by esports players (8, 13, 19). These indicators were among the most frequently reported symptoms in our sample. In the subnetwork structure, depressed mood remained the most upstream node, directly connecting to mental fatigue and anxiety, which were in turn linked to perceived lack of skill, sleep quality, sleep quantity, and physical fatigue. Notably, mental fatigue occupied a structurally important position as a connecting node between a depressed mood and anxiety, and the other sleep-related factors. Fatigue-related indicators were positioned more upstream than sleep problems, rather than the other way around. This pattern is somewhat counterintuitive and deviates from traditional clinical knowledge, which typically frames poor sleep as influencing fatigue (66). In the present network, however, the model placed mental fatigue and related distress indicators more upstream in the estimated dependency structure than sleep quantity and sleep quality. In other words, in the current estimated structure, poor sleep may be positioned as a compound of upstream negative mood and mental fatigue, rather than functioning as an independent organiser of the wider network (67).

One plausible explanation for this finding might be that, in high-stress competitive environments, individuals are often thoroughly fatigued yet too cognitively or physically aroused to sleep well (68). For example, in high-level elite sports, extreme loads, overtraining and insufficient rest are speculated to provoke insomnia-like symptoms (e.g., difficulty falling asleep, restlessness, unrefreshing sleep) despite the athlete's mental and physical exhaustion (69). A similar fatigue-to-sleep pathway in esports may stem from the intense and irregular training regimen characteristic of this environment (40). Professional and aspiring players often engage in prolonged practice sessions, sometimes exceeding 12 hours of predominantly sedentary, screen-focused activity, and often occurs in the absence of structured coaching frameworks or evidence-based training methodologies (17, 28, 70). Moreover, it is not uncommon for esports players to play late into the night, maintaining an irregular sleep schedule and poor sleep hygiene (40). Such a gruelling schedule may result in significant mental and physical exhaustion, potentially mirroring the impact of high training demands of traditional sports (12). However, unlike many traditional sports athletes who are educated early about the importance of rest (71), esports

players operate in a culture that valorises “grinding” (i.e., excessive practice with minimal breaks), often at the expense of other health considerations such as physical activity or sleep (40, 72). This pattern of insufficient and misaligned sleep, combined with sustained late-night arousal from prolonged screen exposure and competitive stress, may create a scenario in which players end the day thoroughly fatigued but yet physiologically and psychologically aroused, making it difficult to obtain quality rest (40, 73). As such, our current network generates several directions for future research to examine the role of mental fatigue in esports, including whether it precedes sleep disturbance and whether this association is shaped by mismanaged training loads, late-night play, and pre-sleep arousal.

4.1 Applied Implications/Future Directions

The present DAG findings should be interpreted as exploratory and hypothesis-generating (i.e., the directed associations should be considered as a provisional and exploratory map of candidate pathways that warrant follow-up research). In this sense, the identified nodes and pathways may warrant closer attention in future longitudinal, experimental, or intervention studies. Three observations may be especially useful for follow-up work. First, mental ill-health symptoms seem to be both prevalent and structurally important in the current network structure as well as in emerging research. Together with game thought-preoccupation emerging as a structural sink node, this pattern suggests that future research should examine whether players with existing distress are drawn to esports because of social, identity-related, or coping functions (i.e., esports-as-coping), whether distress emerges partly through sustained participation in demanding competitive gaming environments (i.e., esports-as-stress), or whether both processes unfold reciprocally over time (e.g. 5, 62, 63 74). Second, emotion regulation and autonomy occupied structurally prominent positions that may merit close examination in future studies of psychosocial functioning in esports, including the possibility that they shape how players experience esports-specific stress and game-related thought preoccupation. Unlike traditional sport, where athletes typically develop within established coaching and team structures, many esports players progress through largely self-directed online play with limited adult guidance. It is plausible that developing in comparative isolation offers fewer structured opportunities to build emotion regulation skills and a stable sense of autonomy. Future work would benefit from exploring this qualitatively across the course of players’ careers. Third, the high prevalence and positioning of mental fatigue suggests that finer-grained measurement of cognitive fatigue, and its connection to sleep and training load, may warrant attention in future work.

4.2 Limitations

While this study provides a novel and comprehensive look at the interplay between esports-specific stressors, mental health outcomes, socio-emotional factors, and sleep disturbances, it is not without limitations. Firstly, the data is cross-sectional in nature, meaning we cannot definitively establish causal relationships or temporal antecedence (54). Although the DAG approach introduces directionality based on conditional dependence and model fit, one should interpret the implied “causal” directions with caution. As such, these cross-sectional models should only serve a hypothesis-generating function,

rather than a hypothesis-testing one (33). Relatedly, the DAG is consistent with a model-derived directed dependency from, for example, depressed mood to anxiety, but this should not be interpreted as evidence that depressed mood temporally or causally produces anxiety (BIC-g = -286.12, dir. = 0.55). In reality, these symptoms likely reinforce each other over time. As DAGs are acyclic in nature and assume directed connections between nodes, they do not take potential feedback loops into account. Furthermore, some edges with directionalities near 50% (e.g., from “DepressedMood” to “Anxiety”; dir. = 0.55) may be prone to flipping to the other side. It therefore remains important to note that although certain variables are located downstream in the DAG network topology (e.g., “GamePreoccupation”), they may still play a causal role in the development of mental ill-health symptoms. Additionally, when interpreting networks estimated from cross-sectional data one must note that the network structure primarily reflects between-person differences. These structures are not necessarily isomorphic with the within-person processes or mechanisms operating in the individuals (30). Longitudinal research is needed to test the directional pathways suggested in the current study, and to see how these interactions evolve over time due to, for example, different career stages, competitive pressure, or other factors.

While we attempted to develop a comprehensive questionnaire, unmeasured variables which are not included in the graph may have a mediating effect and influence the structure of the graph. The measures adopted in the network, although grounded in theory and informed by prior research, were single items for each construct (i.e., one item for autonomy, one for emotion control, etc.). While this choice was intentional in order for the questionnaire to remain manageable for participants, avoid topological overlap across variables, and serve as exploratory work, it does mean that each node is a simplified representation of a much more complex and nuanced phenomenon (e.g., game-related thought preoccupation may not fully equate to clinically problematic gaming). Future studies may need to further investigate the relationship of a more limited, but more detailed, number of variables or subnetworks. Relatedly, future research may consider the use of qualitative interview or diary studies, or longitudinal perceived causal network methodologies to capture the depth of interactions between esports and mental health.

Lastly, although the DAG structure may suggest candidate priorities for follow-up work, the present study cannot determine how intervening on any specific node would affect the rest of the network. Relatedly, our sample was highly heterogenous, consisting of players of all genders (men, women, and nonbinary), ages, performance levels (i.e., recreational to mastery level), and differing geographic regions. As such, the network structure reported in the current study should be understood as an aggregate description of this sample rather than as a universally shared model of esports mental health. While outside the scope of the current study, formal comparative analyses, and ideally, longitudinal, experimental, and intervention designs are needed before any group-specific or practice-oriented conclusions can be drawn.

5. Conclusion

The current study explored the complex, interconnected network structure between esports-specific stressors, psychosocial factors, sleep and fatigue variables and mental ill-health symptoms within a broad esports sample. By combining BGGCM and DAG estimations, we moved beyond prevalences and undirected associations towards an exploratory description of conditional dependency structures, thereby generating hypotheses and suggesting future avenues for longitudinal, experimental, and intervention research. In the network structure, a depressed mood emerged as a notable upstream node, emotion control and a sense of autonomy together appeared as important connecting nodes between upstream affective variables and downstream esports-specific variables, and mental fatigue appeared to be embedded between negative affect and the broader sleep-fatigue cluster. Game-related thought preoccupation appeared as a structural sink node downstream of several psychosocial indicators, pointing to the possibility that it represents a compound indicator of upstream psychosocial strain rather than an organising indicator itself. Taken together, the current findings provide a structured exploratory map of how a set of theoretically selected indicators was organised in a large sample of esports players and highlight specific constructs and pathways that may be worth examining more closely in future validation, longitudinal, experimental, and intervention research.

Declarations

Ethics approval and consent to participate

Institutional ethical approval was granted by the Ethical Committee of Human Sciences of the Vrije Universiteit Brussel (File number ECHW_529-WP1). All participants provided written informed consent before participating in the study.

Consent for publication

Consent to publish anonymous data was obtained from the participants.

Availability of data and materials

Data will be stored in a public repository upon the completion of the project. Data will be available upon reasonable request.

Competing interests

The following co-authors hold affiliation with industry partners: MW, IPR and JR. No additional conflicts are reported.

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CrediT authorship contribution statement

LVR Writing – Original Draft, Software, Formal Analysis, Data Curation, Visualization **MVH** Conceptualization, Methodology, Writing – Review & Editing **MT** Conceptualization, Methodology, Investigation, Writing – Review & Editing **MW** Investigation, Writing – Review & Editing **IPR** Investigation, Writing – Review & Editing **IB** Investigation, Writing – Review & Editing **PD** Writing – Review & Editing **JR** Investigation **OM** Conceptualization, Methodology, Software, Data Curation, Writing – Review & Editing, Supervision **JK** Conceptualization, Methodology, Investigation, Writing – Review & Editing, Supervision, Project administration, Funding acquisition.

All authors read and approved the final manuscript.

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References

1. Pedraza-Ramirez I, Musculus L, Raab M, Laborde S. Setting the scientific stage for esports psychology: a systematic review. Int Rev Sport Exerc Psychol. 2020;13(1):319–52. https://doi.org/10.1080/1750984x.2020.1723122.
2. ISFE Esports. (2021). The Guide to Esports. The Entertainment Software Association. Available from: https://www.videogameseurope.eu/wp-content/uploads/2023/11/Guide-to-Esports-ISFE-ESA-ESA-C-IGEA_small.pdf
3. Granic I, Lobel A, Engels RCME. The benefits of playing video games. Am Psychol. 2014;69(1):66–78. https://doi.org/10.1037/a0034857.
4. O'Gorman K, Benakovic R, Fisher K. Game boys: gaming, esports, and young men's mental health. Masculinities and mental health in young men. Springer Nature; 2024. pp. 93–129. https://doi.org/10.1007/978-3-031-64053-7_4.
5. Leis O, Sharpe BT, Pelikan V, Fritsch J, Nicholls AR, Poulus D. Stressors and coping strategies in esports: a systematic review. Int Rev Sport Exerc Psychol. 2024. https://doi.org/10.1080/1750984x.2024.2386528.
6. Kegelaers J, Trotter MG, Watson M, Pedraza-Ramirez I, Bonilla I, Wylleman P, et al. Promoting mental health in esports. Front Psychol. 2024;15:1342220. https://doi.org/10.3389/fpsyg.2024.1342220.
7. Shulze J, Marquez M, Ruvalcaba O. The biopsychosocial factors that impact esports players' well-being: a systematic review. J Global Sport Manage. 2021;8(2):478–502.

https://doi.org/10.1080/24704067.2021.1991828.

8. Kegelaers J, Mairesse O, Van Ruysevelt L, Trotter M, Watson M, Pedraza-Ramirez I, et al. The mental health status of esports athletes. J Electron Gaming Esports. 2025;3:1–10. https://doi.org/10.1123/jege.2025-0017.
9. Poulus D, Nicholson M, Obine E, Drew M, Fisher K, Vella SA, et al. The state of mental health research in esports: a scoping review. Appl Psychology: Int Rev. 2026;75(1). https://doi.org/10.1111/apps.70055.
10. Keyes CLM. The mental health continuum: from languishing to flourishing in life. J Health Soc Behav. 2002;43(2):207–22. https://doi.org/10.2307/3090197.
11. Birch P, Smith MJ, Arumuham A, Ortiz de Gortari A, Sharpe BT. The prevalence of mental ill health in elite Counter-Strike athletes. J Electron Gaming Esports. 2024;2(1). https://doi.org/10.1123/jege.2024-0006. jege.2024-0006.
12. Monteiro Pereira A, Teques P, Verhagen E, Gouttebarge V, Figueiredo P, Brito J. Mental health symptoms in electronic football players. Sports Med. 2022;52(9):2039–60. https://doi.org/10.1136/bmjsem-2021-001149.
13. Akan B, Alin L, Işık B, Pelin A. The effects of esports on sleep: a systematic literature review. Ovidius University Annals, Series Physical Education & Sport/Science, Movement & Health. 2022;22(2):95–104.
14. Bonnar D, Castine B, Kakoschke N, Sharp G. Sleep and performance in eathletes: for the win! Sleep Health. 2019;5(6):647–50. https://doi.org/10.1016/j.sleh.2019.06.007.
15. Fried EI, Cramer AOJ. Moving forward: challenges and directions for psychopathological network theory and methodology. Perspect Psychol Sci. 2017;12(6):999–1020. https://doi.org/10.1177/1745691617705892.
16. Pedraza-Ramirez I, Ramaker B, Mathorne OW, Watson M, Laborde S. Behind the curtains of elite esports: a case study from a holistic ecological approach to talent development. Case Stud Sport Exerc Psychol. 2024;8(S1):S1–18. https://doi.org/10.1123/cssep.2023-0017.
17. Pedraza-Ramirez I, Sharpe BT, Behnke M, Toth AJ, Poulus DR. The psychology of esports: trends, challenges, and future directions. Psychol Sport Exerc. 2025;81:102967. https://doi.org/10.1016/j.psychsport.2025.102967.
18. Schary DP, Jenny SE, Koshy A. Leveling up esports health: current status and call to action. International Journal of Esports. 2022. Available from: https://www.ijesports.org/article/70/html
19. Smith M, Sharpe B, Arumuham A, Birch P. Examining the predictors of mental ill health in esport competitors. Healthcare. 2022;10(4):1–13. https://doi.org/10.3390/healthcare10040626.
20. Arnau-Soler A, Adams MJ, Clarke T, MacIntyre DJ, Milburn K, Navrady L, et al. A validation of the diathesis-stress model for depression in Generation Scotland. Translational Psychiatry. 2019;9(1). https://doi.org/10.1038/s41398-018-0356-7.
21. Beres NA, Klarkowski M, Mandryk RL. Playing with emotions: a systematic review examining emotions and emotion regulation in esports performance. Proceedings of the ACM on Human-

Computer Interaction. 2023;7(CHI PLAY):558–587. https://doi.org/10.1145/3611041

22. Trotter MG, Coulter TJ, Davis PA, Poulus DR, Polman R. Examining the impact of school esports program participation on student health and psychological development. Front Psychol. 2021;12:807341. https://doi.org/10.3389/fpsyg.2021.807341.
23. Trotter MG, Obine EA, Sharpe BT. Self-regulation, stress appraisal, and esport action performance. Front Psychol. 2023;14:1265778. https://doi.org/10.3389/fpsyg.2023.1265778.
24. Angelo DL, Boas Junior MV, De Freitas Corrêa M, Souza VH, De Paula Moura L, De Oliveira R, et al. Basic psychological-need satisfaction and thwarting: a study with Brazilian professional players of League of Legends. Sustainability. 2022;14(3):1701. https://doi.org/10.3390/su14031701.
25. Hong HJ, Wilkinson G, Rocha CM. The relationship between basic needs satisfaction, self-determined motivation, and burnout in Korean esports players. J Gambl Stud. 2022;39(1):323–38. https://doi.org/10.1007/s10899-022-10132-8.
26. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol. 2000;55(1):68–78. https://doi.org/10.1037/0003-066x.55.1.68.
27. Lemmens JS, Valkenburg PM, Peter J. Development and validation of a game addiction scale for adolescents. Media Psychol. 2009;12(1):77–95. https://doi.org/10.1080/15213260802669458.
28. Watson M, Trotter MG, Laborde S, Leeder TM. I don't believe any qualifications are required: exploring global stakeholders' perspectives towards the developmental experiences of esports coaches. Educ Sci. 2025;15(7):858. https://doi.org/10.3390/educsci15070858.
29. Poulus DR, Sargeant J, Zarate D, Griffiths MD, Stavropoulos V. Burnout, resilience, and coping among esports players: a network analysis approach. Comput Hum Behav. 2024;153:108139. https://doi.org/10.1016/j.chb.2024.108139.
30. Borsboom D, Deserno MK, Rhemtulla M, Epskamp S, Fried EI, McNally RJ, et al. Network analysis of multivariate data in psychological science. Nat Reviews Methods Primers. 2021;1(1). https://doi.org/10.1038/s43586-021-00055-w.
31. Briganti G, Scutari M, McNally RJ. A tutorial on Bayesian networks for psychopathology researchers. Psychol Methods. 2022;28(4):947–61. https://doi.org/10.1037/met0000479.
32. Hevey D. Network analysis: a brief overview and tutorial. Health Psychol Behav Med. 2018;6(1):301–28. https://doi.org/10.1080/21642850.2018.1521283.
33. Heeren A, Lannoy S, Coussement C, Hoebeke Y, Verschuren A, Blanchard MA, et al. A network approach to the five-facet model of mindfulness. Sci Rep. 2021;11(1). https://doi.org/10.1038/s41598-021-94151-2.
34. Burger J, Isvoranu A, Lunansky G, Haslbeck JMB, Epskamp S, Hoekstra RHA, et al. Reporting standards for psychological network analyses in cross-sectional data. Psychol Methods. 2023;28(4):806–24. https://doi.org/10.1037/met0000471.
35. Hallquist MN, Wright AGC, Molenaar PCM. Problems with centrality measures in psychopathology symptom networks: why network psychometrics cannot escape psychometric theory. Multivar

Behav Res. 2019;56(2):199–223. https://doi.org/10.1080/00273171.2019.1640103.

36. Hoffman M, Steinley D, Trull TJ, Sher KJ. Criteria definitions and network relations: the importance of criterion thresholds. Clin Psychol Sci. 2018;6(4):506–16. https://doi.org/10.1177/2167702617747657.
37. Kroenke K, Spitzer RL, Williams JBW. The Patient Health Questionnaire-2. Med Care. 2003;41(11):1284–92. https://doi.org/10.1097/01.mlr.0000093487.78664.3c.
38. Kroenke K, Spitzer RL, Williams JB, Monahan PO, Löwe B. Anxiety disorders in primary care: prevalence, impairment, comorbidity, and detection. Ann Intern Med. 2007;146(5):317. https://doi.org/10.7326/0003-4819-146-5-200703060-00004.
39. Buysse DJ, Reynolds CF, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193–213. https://doi.org/10.1016/0165-1781(89)90047-4.
40. Bonnar D, Lee S, Gradisar M, Suh S. Risk factors and sleep intervention considerations in esports: a review and practical guide. Sleep Med Res. 2019;10(2):59–66. https://doi.org/10.17241/smr.2019.00479.
41. Luo Y, Hutchinson JC, O'Connell CS, Sha Y. Reciprocal effects of esport participation and mental fatigue among Chinese undergraduate students using dynamic structural equation modeling. Psychol Sport Exerc. 2022;62:102251. https://doi.org/10.1016/j.psychsport.2022.102251.
42. Madden D, Harteveld C. Constant pressure of having to perform: exploring player health concerns in esports. In: CHI Conference on Human Factors in Computing Systems. 2021. pp. 1–14. https://doi.org/10.1145/3411764.3445733
43. Mohammadi R, Wit EC. BDgraph: an R package for Bayesian structure learning in graphical models. J Stat Softw. 2019;89(3). https://doi.org/10.18637/jss.v089.i03.
44. Mohammadi R, Wit EC, BDgraph. Bayesian structure learning in graphical models using birth-death MCMC. Version 2.73 [R package]. CRAN; 2024. Available from: https://cran.r-project.org/package=BDgraph
45. Scutari M, Silander T, bnlearn. Bayesian network structure learning, parameter learning and inference. Version 5.0.2 [R package]. CRAN; 2025. Available from: https://www.bnlearn.com/
46. Briganti G, Kempenaers C, Braun S, Fried EI, Linkowski P. Network analysis of empathy items from the interpersonal reactivity index in 1973 young adults. Psychiatry Res. 2018;265(7):87–92. https://doi.org/10.1016/j.psychres.2018.03.082.
47. Scutari M, Denis J, Bayesian. networks. 2022. https://doi.org/10.1201/9780429347436
48. Kass RE, Raftery AE. Bayes factors. J Am Stat Assoc. 1995;90(430):773–95.
49. R Core Team. R: a language and environment for statistical computing. Version 4.4.3 [computer software]. Vienna: R Foundation for Statistical Computing. 2024. Available from: https://www.R-project.org/

50. Csárdi G, Nepusz T, Traag V, Horvát S, Zanini F, Noom D et al. igraph: network analysis and visualization in R. Version 2.1.4 [R package]. CRAN; 2025. Available from: https://cran.r-project.org/package=igraph
51. Epskamp S, Fried EI. bootnet: bootstrap methods for various network estimation routines. Version 1.6 [R package]; 2024. Available from: https://cran.r-project.org/web/packages/bootnet/index.html
52. Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D. qgraph: network visualizations of relationships in psychometric data. Version 1.9.8 [R package]. Journal of Statistical Software. 2023;48(4):1–18. Available from: https://cran.r-project.org/package=qgraph
53. Diestel R. Graph theory. 5th ed. Springer; 2017. https://doi.org/10.1007/978-3-662-53622-3.
54. McNally RJ. Network analysis of psychopathology: controversies and challenges. Ann Rev Clin Psychol. 2021;17:31–53. https://doi.org/10.1146/annurev-clinpsy-081219-092850.
55. Quinn CJ, Pinar A, Gao J, Su L. Sparse approximations of directed information graphs. In: 2022 IEEE International Symposium on Information Theory (ISIT). 2016. pp. 1735–1739. https://doi.org/10.1109/isit.2016.7541596
56. Schinke RJ, Stambulova NB, Si G, Moore Z. International society of sport psychology position stand: athletes' mental health, performance, and development. Int J Sport Exerc Psychol. 2018;16(6):622–39. https://doi.org/10.1080/1612197x.2017.1295557.
57. Gouttebarge V, Castaldelli-Maia JM, Gorczynski P, Hainline B, Hitchcock ME, Kerkhoffs GM, et al. Occurrence of mental health symptoms and disorders in current and former elite athletes: a systematic review and meta-analysis. Br J Sports Med. 2019;53(11):700–6. https://doi.org/10.1136/BJSPORTS-2019-100671.
58. Kessler RC, Wai TC, Demler O, Walters EE. Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. Arch Gen Psychiatry. 2005;62(6):617–27. https://doi.org/10.1001/ARCHPSYC.62.6.617.
59. Ryan RM, Deci EL. Autonomy is no illusion: self-determination theory and the empirical study of authenticity, awareness, and will. In: Greenberg J, Koole SL, Pyszczynski T, editors. Handbook of experimental existential psychology. Guilford Press; 2004. pp. 449–479. Available from: https://psycnet.apa.org/record/2004-21900-028
60. Drew M, Bennett KJ, Polman R, Poulus DR. Stress and coping in elite esports: a diary study of stress, coping and coping effectiveness. Psychol Sport Exerc. 2025;102937. https://doi.org/10.1016/j.psychsport.2025.102937.
61. Poulus DR, Bennett KJ, Swann C, Moyle GM, Polman RC. The influence of an esports-adapted coping effectiveness training (E-CET) on resilience, mental health, and subjective performance among elite League of Legends players: a pilot study. Psychol Sport Exerc. 2023;69:102510. https://doi.org/10.1016/j.psychsport.2023.102510.
62. Bányai F, Griffiths MD, Demetrovics Z, Király O. The mediating effect of motivations between psychiatric distress and gaming disorder among esport gamers and recreational gamers. Compr Psychiatr. 2019;94:152117. https://doi.org/10.1016/j.comppsych.2019.152117.

63. Bányai F, Zsila Á, Kökönyei G, Griffiths MD, Demetrovics Z, Király O. The moderating role of coping mechanisms and being an e-sport player between psychiatric symptoms and gaming disorder: online survey. JMIR Mental Health. 2021;8(3):e21115. https://doi.org/10.2196/21115.
64. Goodwin H, Haycraft E, Meyer C. Emotion regulation styles as longitudinal predictors of compulsive exercise: a twelve month prospective study. J Adolesc. 2014;37(8):1399–404. https://doi.org/10.1016/j.adolescence.2014.10.001.
65. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, et al. Prevention, diagnosis, and treatment of the overtraining syndrome. Med Sci Sports Exerc. 2013;45(1):186–205. https://doi.org/10.1249/mss.0b013e318279a10a.
66. Riemann D, Baglioni C, Bassetti C, Bjorvatn B, Groselj LD, Ellis JG, et al. European guideline for the diagnosis and treatment of insomnia. J Sleep Res. 2017;26(6):675–700. https://doi.org/10.1111/jsr.12594.
67. Alvaro PK, Roberts RM, Harris JK. A systematic review assessing bidirectionality between sleep disturbances, anxiety, and depression. Sleep. 2013;36(7):1059–68. https://doi.org/10.5665/sleep.2810.
68. Riemann D, Spiegelhalder K, Feige B, Voderholzer U, Berger M, Perlis M, et al. The hyperarousal model of insomnia: a review of the concept and its evidence. Sleep Med Rev. 2009;14(1):19–31. https://doi.org/10.1016/j.smrv.2009.04.002.
69. Kreher JB, Schwartz JB. Overtraining syndrome. Sports Health: Multidisciplinary Approach. 2012;4(2):128–38. https://doi.org/10.1177/1941738111434406.
70. DiFrancisco-Donoghue J, Balentine J, Schmidt G, Zwibel H. Managing the health of the esport athlete: an integrated health management model. BMJ Open Sport Exerc Med. 2019;5(1):e000467. https://doi.org/10.1136/bmjsem-2018-000467.
71. Eccles DW, Balk Y, Gretton TW, Harris N. The forgotten session: advancing research and practice concerning the psychology of rest in athletes. J Appl Sport Psychol. 2022;34(1):3–24. https://doi.org/10.1080/10413200.2020.1756526.
72. Abbott C, Watson M, Birch P. Perceptions of effective training practices in League of Legends: a qualitative exploration. J Electron Gaming Esports. 2022;1(1). https://doi.org/10.1123/jege.2022-0011.
73. Cain N, Gradisar M. Electronic media use and sleep in school-aged children and adolescents: a review. Sleep Med. 2010;11(8):735–42. https://doi.org/10.1016/j.sleep.2010.02.006.
74. Trotter MG, Linnér L, Jonasson K, Kegelaers J, Watson M, Østergaard LD, et al. Sanctuary to sinkhole and back again: video gaming and esport as a transition environment for young people at risk of marginalization. Front Psychol. 2026;17. https://doi.org/10.3389/fpsyg.2026.1793190.

Figures

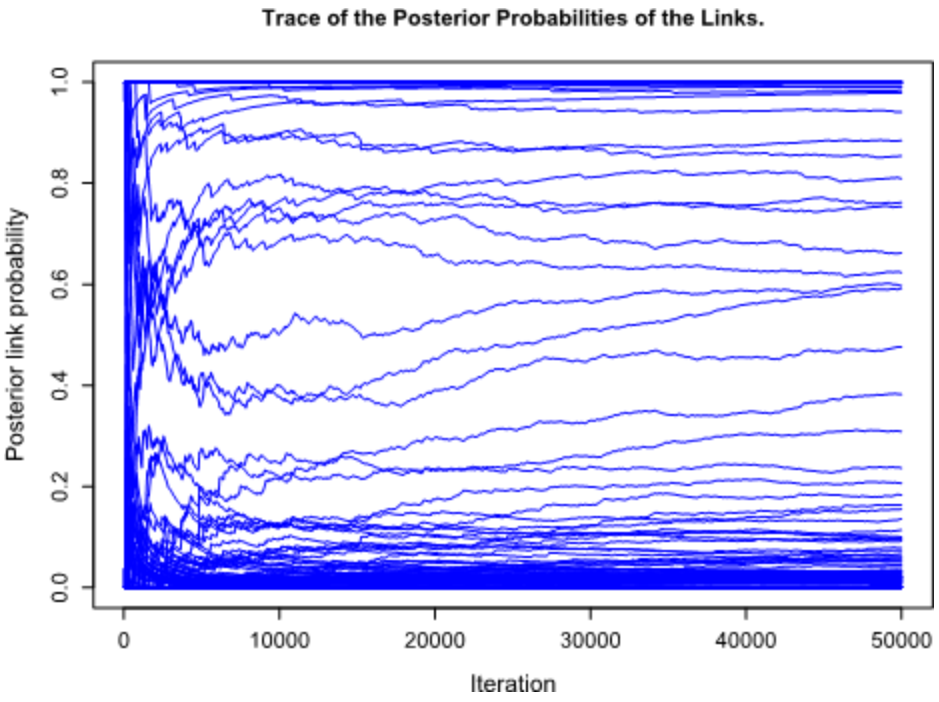


Figure 1

BGGCM Posterior Probabilities convergence plot of all possible links

Description: Convergence plot from the BDgraph plotcoda function. Each line represents the cumulative occupancy fraction (posterior inclusion probability) of a possible edge in the graph across BDMCMC iterations.

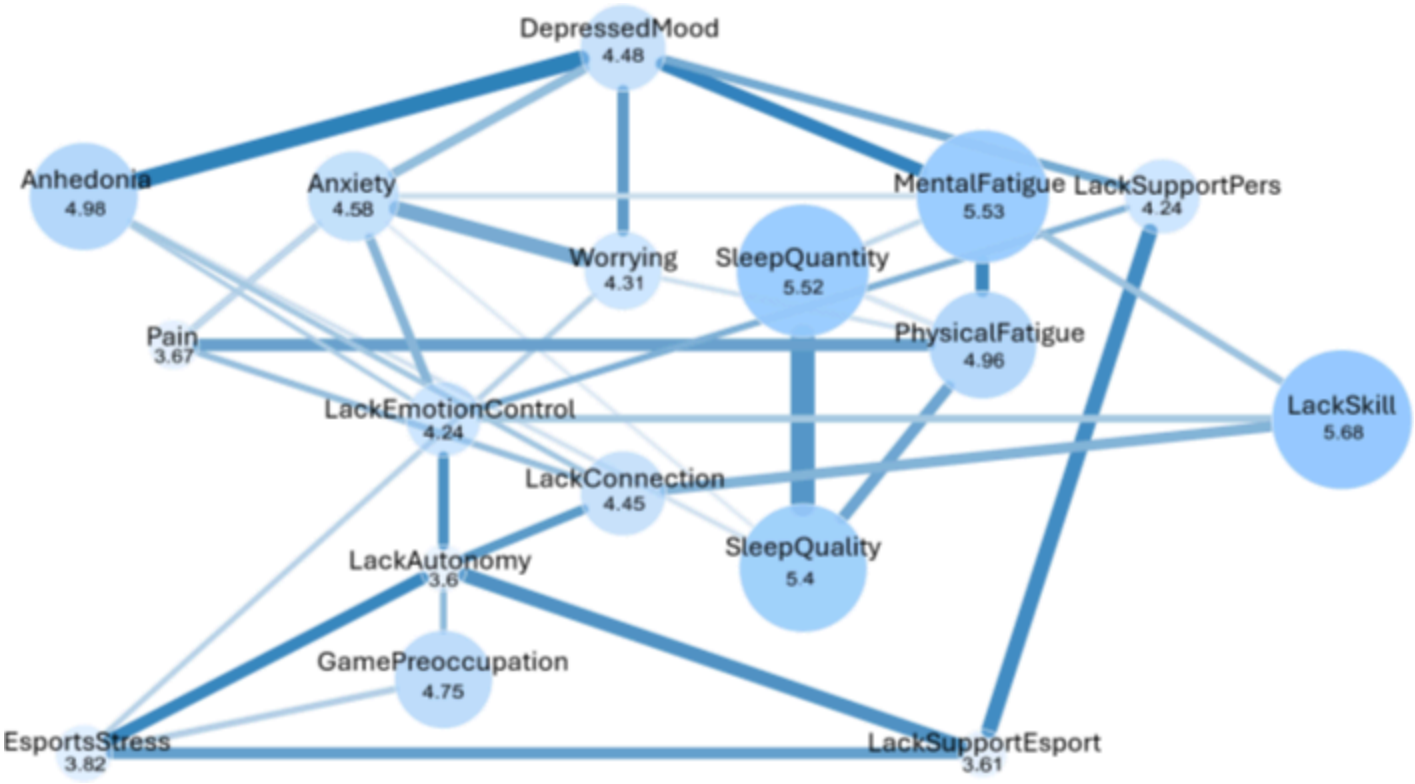


Figure 2

Bayesian Gaussian Graphical Copula Model of the bespoke questionnaire data (edge width based on partial correlations and node size based on mean score)

Description: Bayesian Gaussian Graphical Copula Model (BGGCM) network visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each edge depicts an estimated partial correlation between two nodes, controlling for all other variables in the model; edge presence and thickness reflect the strength of these conditional associations.

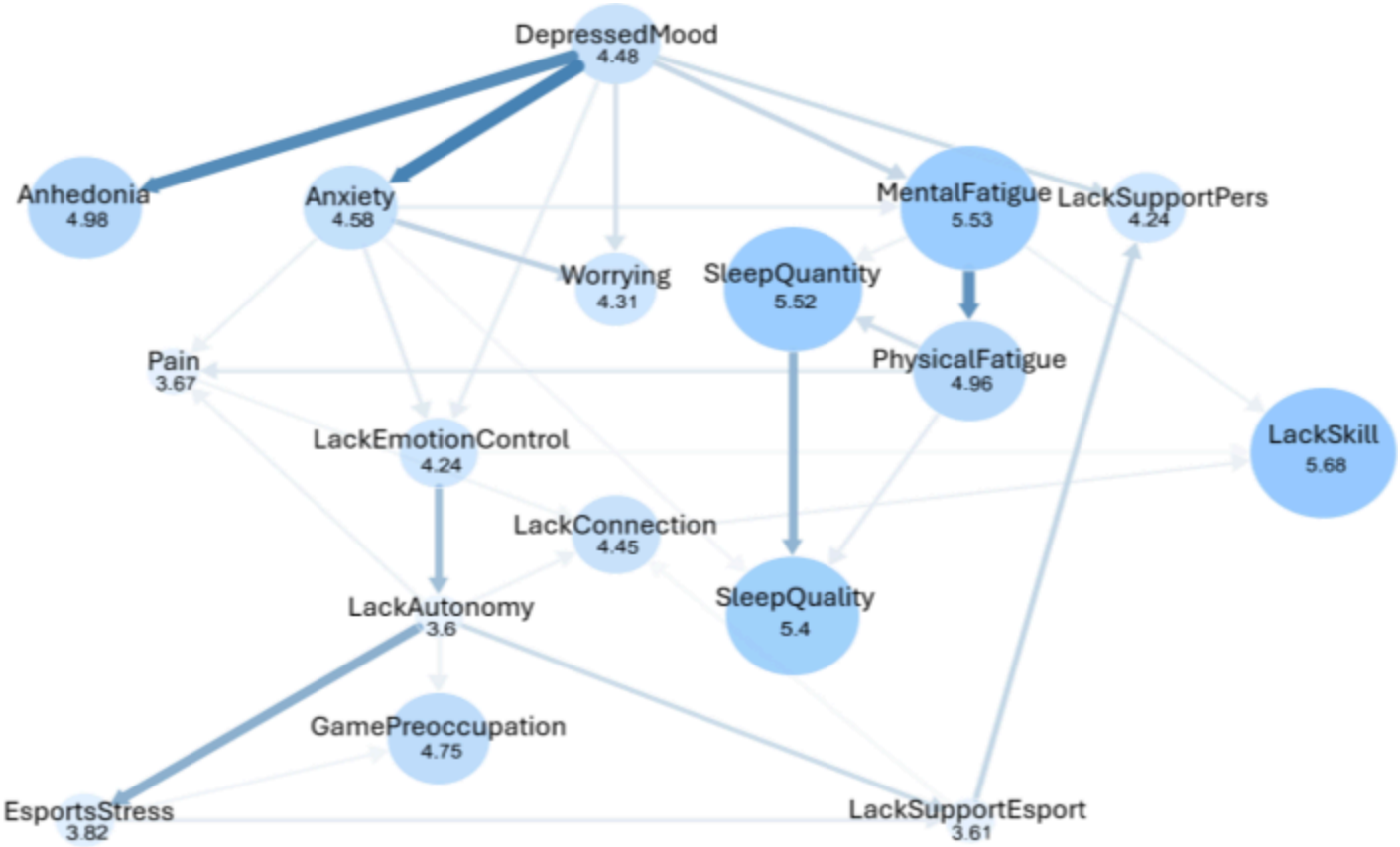


Figure 3

Directed Acyclic Graph of the bespoke questionnaire data – based on BIC-g scores

Description: Directed acyclic graph (DAG) network visualisation. Each node represents a questionnaire item and its size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child in the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations.

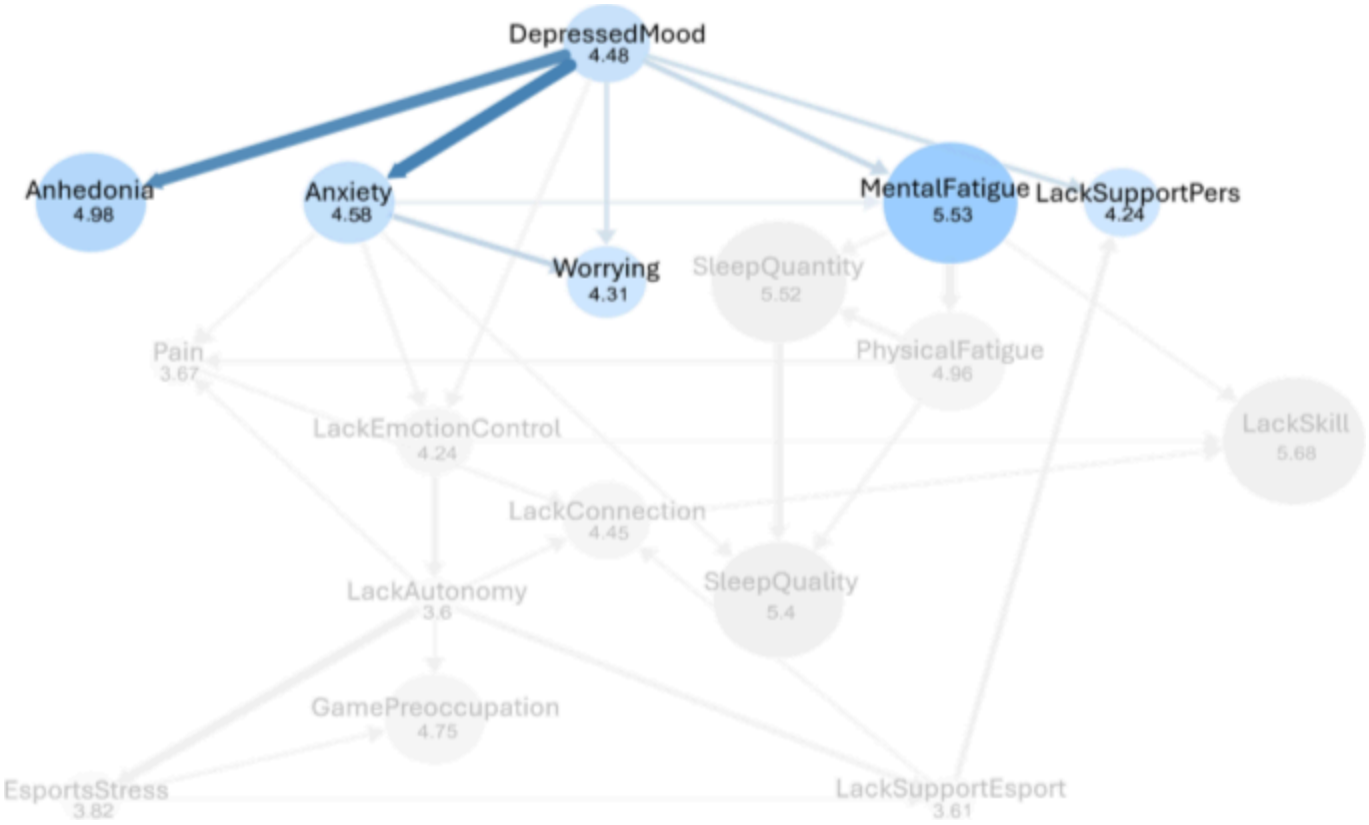


Figure 4

Psychopathological subnetwork – edge thickness based on BIC-g score

*Description:*Psychopathological subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations. This psychopathological subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

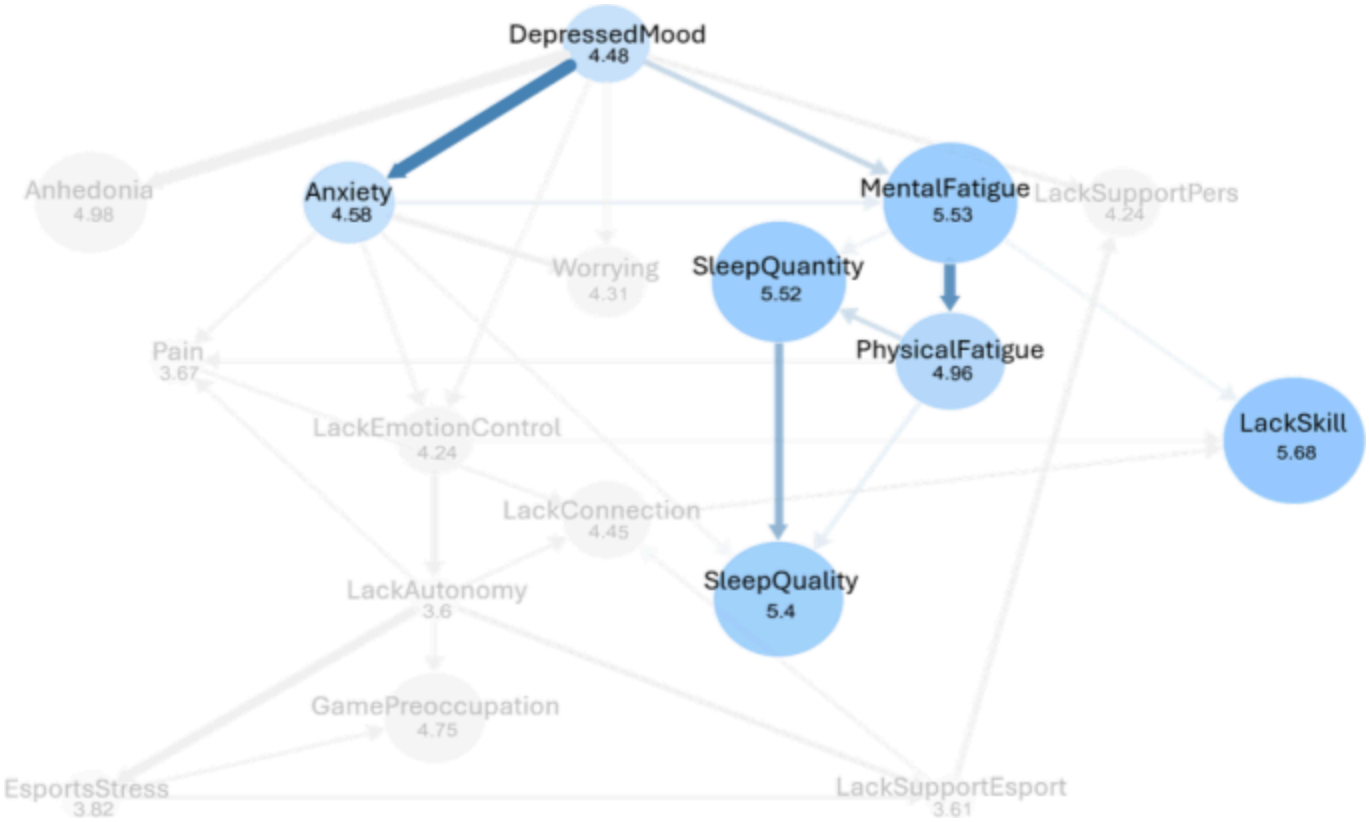


Figure 5

Somnological subnetwork – edge thickness based on BIC-g score

Description: Somnological subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations. This somnological subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

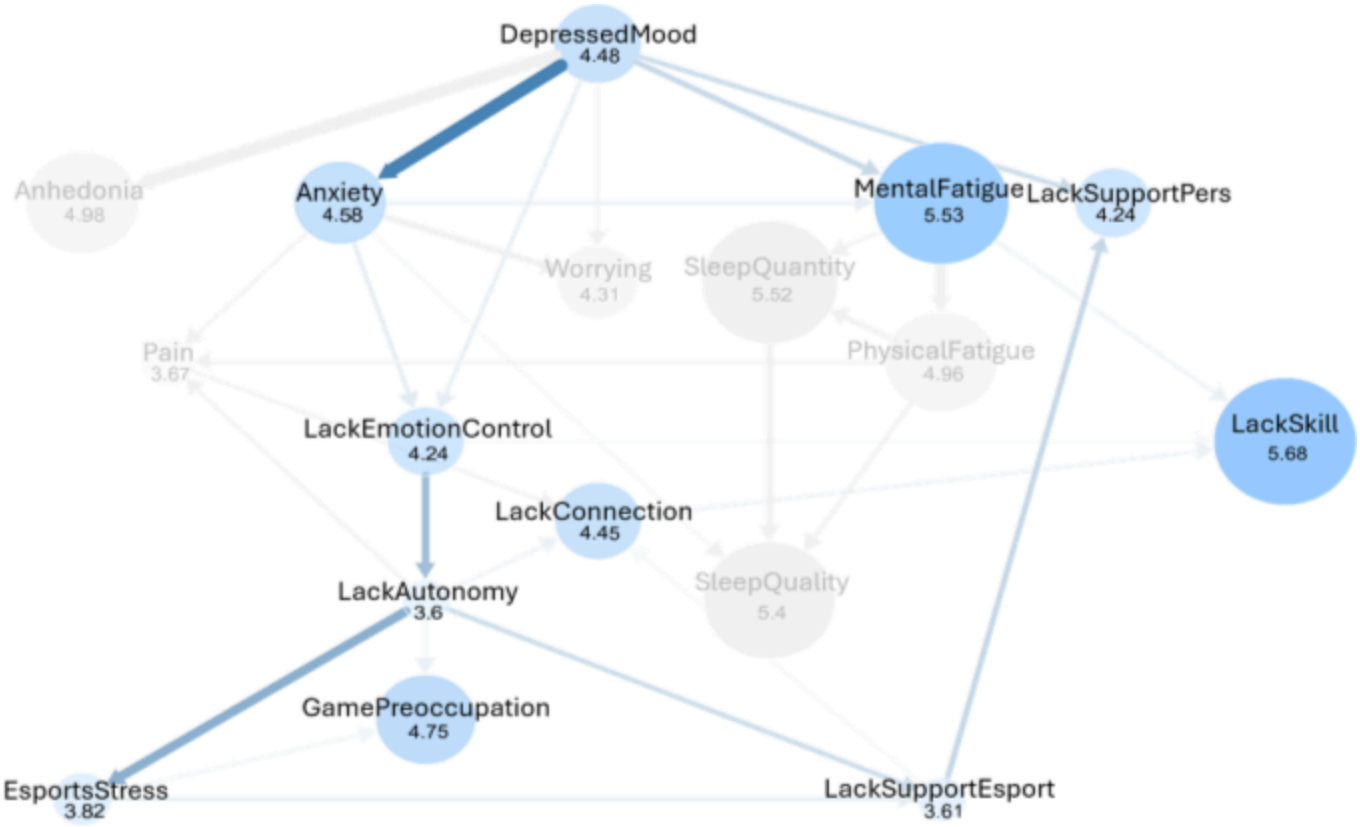


Figure 6

Esports-specific subnetwork – edge thickness based on BIC-g score

Description: Esports-specific subnetwork visualisation. Each node represents a questionnaire item and node size reflects the item mean. Each directed edge (arrow) depicts an estimated conditional dependency from parent to child within this portion of the network; arrow thickness reflects the change in the global Bayesian Information Criterion when that edge is removed from the network across the bootstrapped DAG estimations. This esports-specific subnetwork remains part of the larger model, but provides a focused lens on domain-specific processes within the broader network.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplemetaryMaterials.docx