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Burnout profiles among esports players: Associations with mental toughness and resilience

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ABSTRACT

The present study investigated burnout among esports players and its association with mental toughness and resilience. Esports players ($N = 453$; $M_{age} = 23.0$, $SD = 4.18$; in the top 40% of in-game rank) from seven team-based esports completed the Athlete Burnout Scale (ABO-S), Mental Toughness Questionnaire 18 (MTQ-18), and the Connor-Davidson Resilience Scale (CD-RISC-10). Latent profile analysis identified three distinct burnout profiles: "low burnout risk" (LBR; 33.8%), "medium burnout risk" (MBR; 28.0%), and "high burnout risk" (HBR; 38.3%). Low burnout profiles were associated with higher mental toughness and resilience. The LBR profile was characterized by low levels of reduced accomplishment (RA), physical exhaustion (PE), and negative feelings (NF), while [MBR and HBR reported similar PE and NF scores but] differed in RA, with HBR showing the highest RA and total burnout. This study is the first to show distinct burnout profiles among esports players, indicating a significant prevalence of burnout symptoms. This should be monitored by both players and support staff (e.g. club managers, programme managers, and high-performance support staff). Additionally, mental toughness and resilience appear to play a protective role against burnout.

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Esports

Esports (i.e., professional and competitive playing of video games) have emerged as a major international sporting activity (Pedraza-Ramirez et al., 2020). According to recent projections, esport audience numbers are expected to increase towards 650 million by 2025, with a growth rate of 8.1% per year (Newzoo, 2022). A catalyst for the growth of the esports industry is the increasing popularity of professional tournaments (Pedraza-Ramirez et al., 2020). For example, the 2021 League of Legends (LoL) "Worlds" reported peaking at nearly 74 million concurrent viewers (Fudge, 2021). Outside of professional esports, esports players compete through their game's internal ranking system (in-game rank). Similar to an Elo rating in chess, in-game rank is a measure of a player's proficiency that often takes into account the results of previous games and the rating of opponents (this varies between esports). Players competing and training to improve their ranks or win competitions have reported spending more than 30 hours per week practising to optimise their performance (Pluss et al., 2022).

Esports participation differs from video game participation as there is a clear competitive motivator for play (Trotter et al., 2021). Players competing in esports at the competitive level (via in-game rank) and the professional level (via organised competitions) have reported experiencing various stressors and mental ill-health (Birch et al., 2024; Poulus & Polman, 2022; Smith et al., 2022). A mental health condition that is being increasingly reported by esports players and receiving increased academic attention is psychological burnout (Poulus et al., 2024; Smith et al., 2022). Personality factors (i.e., resilience and burnout) have been shown to impact the burnout experiences of both traditional sports athletes (Gustafsson et al., 2011) and esports players (Poulus et al., 2024). To further the understanding of burnout among esports players, the present study investigated burnout and the influence of resilience and mental toughness among esports players.

Athlete burnout

In traditional sports, psychological burnout is associated with numerous adverse consequences, including sports dropout, reduced performance, and more severe mental health conditions like anxiety and depression (Gustafsson et al., 2017; Sarmento et al., 2021). Generally defined as a cognitive-affective syndrome, burnout was initially conceptualised as having three factors, (i) a reduced sense of accomplishment, (ii) devaluing or resenting their sport, and (iii) experiencing physical and emotional exhaustion (Raedeke, 1997). Burnout has also become a concern among esports players, and professional

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players have retired or stepped back from competition to cope with burnout (Stubbs, 2020). Recent research into esports performance and mental health has also reported burnout. Elite esports athletes have reported actively reducing the amount of training they perform to manage burnout symptoms (Poulus et al., 2021b). Burnout strongly predicted general symptoms of anxiety and depression, severe symptoms of depression, and psychological distress among esports players across *Counterstrike: Global Offensive, Valorant*, and *Rainbow Six Siege* (Smith et al., 2022). It appears that burnout in esports is an area that requires further investigation.

The most frequently used measure to assess athlete burnout is the Athlete Burnout Questionnaire (ABQ; Raedeke, 1997; Raedeke & Smith, 2009). However, concerns have been raised regarding the physical and emotional subscale of the ABQ. More specifically, a subscale that combines physical and emotional exhaustion into one factor might not be able to distinguish between players who experience physical or emotional exhaustion (Isoard-Gautheur et al., 2018). In response to these concerns, the Athlete Burnout Scale (ABO-S) was developed (Isoard-Gautheur et al., 2018). The ABO-S assesses the mental and emotional strain of competition more accurately, assessing three factors of burnout (i) *reduced sense of accomplishment*, characterised by feelings of inefficacy and a tendency to evaluate oneself negatively based on athletic performance and achievements; (ii) *physical exhaustion*, characterised as feeling physically drained in response to the demands of training and/or competitions; and (iii) *negative feelings towards sport*, characterised as a lack of emotional energy and negative attitudes towards sports that athletes may experience in relation to the demands of training and/or competitions. Adapting the *negative feeling towards sport* factor to include an emotional component is particularly relevant for research among esports players because esports are predominantly fine-motor and cognition-dependent with minimal reliance on physicality.

Recently, Poulus et al. (2024) explored the structure and influence of resilience, stress coping, and burnout among esports players using network analysis. Their results showed that resilience factors were negatively associated with multiple burnout symptoms and positively correlated with multiple coping strategies. More specifically, resilience was positively associated with problem-focused, emotion-focused, and avoidance coping. Moreover, at the burnout factor level, RA was negatively associated with resilience and positively associated with avoidance coping. Avoidance coping in previous esports and traditional sports research has been associated with decreased performance and poorer mental health (Madigan et al., 2020; Nicholls et al., 2016; Poulus et al., 2020). Combined, these results suggest a relationship between lower resilience, maladaptive coping (i.e., avoidance coping), and RA (Poulus et al., 2024). However, while network analysis is effective for understanding complex relationships between variables, it assumes heterogeneity across the sample. Network analysis does not allow for the exploration of identifying heterogeneity within a sample, which (as highlighted by Stavropoulos et al., 2020) is present among various types of internet users. Future research into esports players' experience of burnout needs to explore different types of burnout experiences among esports players to support the development of tailored interventions.

Mental toughness and resilience

Traditional sports athletes' experience of burnout can be influenced by personality factors (Gustafsson et al., 2011). Two influential dispositions in sports/esports success that might predict mental health risks are mental toughness (Poulus et al., 2020) and resilience (Fasey et al., 2021), which appear to be protective factors aiding mental health. Mental toughness is broadly defined as values, attitudes, behaviours, and emotions that allow the individual to be their best self in the face of challenges and in favourable situations (Gucciardi et al., 2008). Esports players with higher levels of mental toughness report utilising more adaptive coping strategies and have higher levels of in-game achievement (Poulus et al., 2020). In traditional sports, higher levels of mental toughness have been associated with fewer symptoms of burnout (Gerber et al., 2018; Madigan & Nicholls, 2017).

Resilience, as distinct from mental toughness, is characterised by behaviours and mental processes that protect players from the potential negative effects of stress and pressure (Fletcher & Sarkar, 2013). Although resilience has not been empirically investigated among esports players, it has been found that gamers with higher levels of resilience report lower levels of internet gaming disorder (Canale et al., 2019). Moreover, resilience has been shown to moderate traditional sports athletes' experience of stress and burnout, supporting players to better cope with stress and experience fewer burnout symptoms (Wu et al., 2022). While more research is needed, it appears that mental toughness and resilience may be associated with lower levels of mental ill-health and could predict more positive mental health outcomes (Fasey et al., 2021; Gucciardi, 2017; Poulus et al., 2020).

Latent profile analysis

Although understanding the associations between variables such as burnout, resilience, and mental toughness might be helpful, studies have reported significant individual differences based on types of internet users (Stavropoulos et al., 2021). These users, including esports players, appear to fall into distinguished types or modes of internet (Kovacs et al., 2022; Tullett-Prado et al., 2021). For example, in a video game population, three distinct psychological distress profiles, distinguished by depression, anxiety, and stress levels, were found (Kovacs et al., 2022). Kovacs et al. (2022) reported high, medium, and low distress profiles, each with varying symptom severity and differing internet gaming disorder risk. Such studies have not been conducted to profile esports players and can be explored using latent profile analysis (LPA). LPA, a specialised type of finite mixture models, uses results on a test and examines it to find patterns and groupings of participants who respond in similar ways, and then it tests generated models that assume those groupings, identifying whether or not they fit the data. In doing so, LPA can identify homogenous subgroups of participants in a dataset based on their responses to a given measure (Tullett-Prado et al., 2021).

These features make LPA particularly suitable for initially investigating the patterns of burnout and burnout factors (i.e., reduced sense of accomplishment, physical exhaustion, and negative feelings towards sport) among esports players.

Aims and hypotheses

As aforementioned, Poulus et al. (2024) explored the resilience, coping, and burnout using network analysis among esports players. While offering an innovative approach to exploring burnout in esports, the findings did not explore heterogeneity that might exist within the sample and therefore the findings lacked specificity and applicability. The present study builds on this research by using LPA to explore the specific burnout profiles that may exist among esports players. More specifically, the present study investigated burnout and the influence of specific personality factors (i.e., resilience and mental toughness) among esports players. The first aim was to explore the various profiles of burnout that exist among esports players (i.e., can esports players be described by different distress profiles/typologies?). The second aim was to expand empirical knowledge regarding how psychological burnout profiles may relate to mental toughness and resilience. To address these aims, the following research questions/hypotheses were explored:

RQ1: How many burnout profiles are there considering burnout factors (physical exhaustion, reduced sense of accomplishment, and negative feelings towards sport)?

RQ2: What proportion of esport players is in each profile based on the three burnout factors?

H1: Esports players with higher levels of burnout will show lower mental toughness and resilience levels (Gucciardi, 2017; Poulus et al., 2020)

Methods

Participants

A sample of 696 esport players was initially recruited. Of those, 243 were excluded for insufficient or inadequate responses (e.g., questionnaires were completed too quickly). The sample comprised 453 English-speaking adult esports players. Participants' ages ranged from 18–52 years ($M = 23.0$, SD = 4.18) and included 372 males (82.1%, $M_{age} = 22.9$, SD = 4.3), 74 females (16.3%, $M_{age} = 23.9$, SD = 3.7), and seven nonbinary (1.5%, $M_{age} = 22.0$, SD = 2.4). In line with previous research on competitive esports players by Poulus et al. (2020, 2022), participants were in the top 40% (as determined by in-game rank) of one of seven team-based esports: *LoL* ($n = 282$), *Valorant* ($n = 50$), *Rainbow 6 Siege* (*R6S*; $n = 46$), *Apex Legends* ($n = 20$), *Counterstrike: Global Offensive* (*CS:GO*, $n = 20$), *DOTA 2* ($n = 19$), and *Overwatch* (*OW*; $n = 16$). Participants were located across 66 different countries, with the majority of participants living in the USA ($n = 167$), Australia ($n = 63$), UK ($n = 22$), Germany ($n = 20$), and Canada ($n = 18$). Half of the sample reported playing more than 14 hours a week (between 14–50+ hours). More specifically, 42 reported playing 10 hours a week (9.3%), 34 reported playing 20 hours a week (7.5%), and 30 reported playing 8 hours a week (6.6%; See Supplementary Table 1 for full distribution of hours per week playing esports). The results of the survey can be considered representative when they accurately reflect the characteristics of the overall population. To ensure this, it is important to calculate the minimum sample size required based on factors such as the desired margin of error, confidence level, and standard deviation. For a sample of 453 individuals, the maximum random sampling error at the 95% CI, SD = 0.5 (z = 1.96) is 4.6%, which is acceptable based on the literature (Hill, 1998). The present study utilised different variables in a dataset initially compiled and made available by Poulus et al. (2024).

Measures

Socio-demographic variables

Socio-demographic questions included age, gender, esport title, and in-game rank. Players outside the top 40% of their chosen esport (as determined by self-reported in-game rank) were unable to continue. In-game rank cut-offs for each esport game were as follows: *League of Legends* > Silver 1, *Apex Legends* > Platinum 4, *Valorant* > Silver 3, *Rainbow 6 Siege* > Gold 1, *DOTA 2* > Archon 4, *Overwatch* > 2500SR, *Counterstrike: Global Offensive* > Gold Nova Master (see supplementary files for distribution of in-game rank frequencies between esports).

Mental toughness

The Mental Toughness Questionnaire 18 (MTQ-18; Dagnall et al., 2019) was used to assess mental toughness. The MTQ-18 comprises 18 items (e.g., *"I generally feel in control"*) rated on a 5-point Likert scale from 1 (*Strongly disagree*) to 5 (*Strongly agree*). Items on the MTQ-18 assess 4C's conceptualisation of mental toughness: challenge, commitment, control (emotion/life), and confidence (interpersonal/ability). Scores range from 18–90, and higher total scores indicate greater mental toughness (Clough et al., 2002). The MTQ-18 has been used to assess mental toughness in several populations (Dagnall et al., 2019;

Table 1. Mean, standard deviation, Conbach's α, and McDonald's ω for resilience, mental toughness, and burnout questionnaires.

Scale	Mean	Standard Deviation	Conbach's α	McDonald's ω
CD-RISC 10	3.52	0.65	0.84	0.84
MTQ-18	3.08	0.49	0.78	0.78
ABO-S	2.78	0.69	0.90	0.90

see; Farnsworth et al., 2022 for a review). In the present study, internal consistency was acceptable (α = 0.77).

Resilience

The Connor-Davidson Resilience Scale (CD-RISC-10) was used to assess resilience (Connor & Davidson, 2003). The CD-RISC-10 is a unidimensional scale that comprises 10 items (e.g., *"I can deal with whatever comes my way"*) rated on a 5-point Likert scale from 0 (*not true at all*) to 4 (*true nearly all the time*). Scores range from 0–40, and a higher total score indicates greater resilience. This scale has been widely used among athletes and has good internal validity (α=.85; D. R. Poulus et al., 2024). In the present study, internal consistency was very good (α=.84). The CD-RISC-10 is the most widely used and validated measure of resilience across various sporting settings (Nooripour et al., 2022; see; Gonzalez et al., 2016 for a review).

Burnout

The Athlete Burnout Scale (ABO-S) was used to assess burnout levels (Isoard-Gautheur et al., 2018). The ABO-S comprises 15 items and has three factors, each assessed using five-item subscales: reduced sense of accomplishment (RA; *"I am not performing up to my abilities"*), physical exhaustion (PE; *"I am not performing up to my abilities"*), and negative feelings towards sport (NF; *"I feel wearied"*). Each item is rated on a 5-point Likert scale, ranging from 1 (*almost never*) to 5 (*almost always*). Scores range from 15 to 75, with higher scores indicating greater burnout. The scale has good construct validity and reliability (Isoard-Gautheur et al., 2018). In the present study, internal consistency was excellent (α = 0.90). See Table 1 for means, standard deviations, Cronbach's α, and McDonald's ω for all three scales.

Procedure

Institutional ethical approval was received from the first author's university ethics committee (Ref:2022/085). The study was advertised online via social media (*Twitch, YouTube, Reddit, Twitter*) through a recruitment video (https://x.com/DylanPoulus/status/1545206901478420480) and written posts (July 2022). Potential participants were directed via URL to *Qualtrics* to complete an online survey. Before beginning the survey, participants were directed to the plain language information statement clearly stating the study's aims, voluntary participation, right to withdraw, and informed consent. Informed consent was confirmed by participants ticking a box before beginning the survey. Participants could opt in to a random prize draw upon successfully completing the survey. As part of data collection for the larger data collection survey from which the present study sampled, participants completed 73 items (including additional surveys assessing stress, stress appraisal, coping, and coping effectiveness). Participants typically completed the survey in 20–30 minutes. Participants were unable to complete the survey if they were aged below 18 years or did not have an in-game rank above the cut-off ranks (top 40% for each esport). Participants were not asked for any information that could be used to identify them, and all data were stored securely online via the *Qualtrics* platform.

Statistical analysis

Incomplete or suspect survey responses were initially removed from the dataset (*n*=243). To explore RQ1 and RQ2, the PE, RA, and NF factors assessed by the ABO-S were employed as indicators for a latent profile analysis (LPA) using the TidyLPA CRAN package in R (Rosenberg et al., 2019). LPA was selected for its modelling methodology and enables the identification of naturally homogeneous subgroups (i.e., profiles) within a population using meaningful descriptors or characteristics (McLachlan, 1987). LPA uses a Maximum Likelihood Estimator (MLE; to estimate the parameters of the model that maximise the likelihood of the observed data, thereby identifying the most probable grouping of individuals into latent classes based on their responses) to determine the likelihood of each esports player's membership in specific profiles, based on their burnout symptoms. TidyLPA was chosen for its capability to estimate the ideal relationships among indicators across various profiles, such as means (i.e., average levels of burnout), variances (i.e., the degree of burnout variation within profiles), and covariances (i.e., variability of burnout across profiles). Table 2 shows four potential combinations of parameterisations of variance-covariance structures that can be estimated with TidyLPA to obtain the optimal number of profiles (Celeux & Soromenho, 1996).

The process for selecting the ideal number of latent profiles is sequential. The first step of identifying the best combination of parameters (including [un]constrained profile mean, variance, and covariance) through comparing models based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Approximate Weight of Evidence Criterion (AWE), Classification

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

Model	Variances	Covariances	Parameterisation Type
1	Equal	Fixed to 0	Class-invariant diagonal parameterisation model (CIDP). The CIDP model assumes that there should be no estimation of relationships among model indicators (with covariances fixed at zero). Additionally, it is assumed that different profiles will exhibit qualitative similarity, with equal variances.
2	Varying	Fixed to 0	Class-varying diagonal parameterisation model (CVDP). The CVDP model assumes that there should be no estimation of relationships among model indicators (with covariances fixed at zero). Furthermore, it is assumed that different profiles will exhibit qualitative differences, with varying variances.
3	Equal	Equal	Class-invariant unrestricted parametrisation model (CIUP). The CIUP model allows indicators to co-vary within profiles, while the variances and covariances are constrained to be equal across different profiles.
6	Varying	Varying	Class varying unrestricted parameterisation (CVUP). The CVUP model allows all indicators to co-vary within profiles, and the variances and covariances (i.e., residual correlations) are allowed to differ across profiles. Essentially, the CVUP model assumes the presence of relationships between model indicators within and between latent profiles that should be estimated (with varying covariances). It also assumes that different profiles will exhibit qualitative differences, including variations in variances.

Likelihood Criterion (CLC), and Kullback Information Criterion (KIC) with lower values indicative of a better fit (see Supplementary Table 2 full a explanation of model parameters). The second step assesses the ideal number of profiles in the model via the bootstrapped likelihood ratio test (BLRT) to determine if adding an extra latent profile results in a significant increase in fit (with $p < .05$ as an indication of improved fit; Celeux & Soromenho, 1996). Finally, the standardised entropy criterion (h) was utilised to evaluate the degree of heterogeneity within the latent profiles, where a range of 0.40–0.60 indicates low entropy, 0.60–0.80 indicates medium entropy, and values exceeding .80 indicate high entropy (Celeux & Soromenho, 1996; Clark & Muthén, 2009). To test H_1, two one-way ANOVAs were conducted to examine differences in mental toughness and resilience between the different burnout profiles. Post hoc analyses were performed to explore any differences. To account for the inflated Type 1 error, a Bonferroni adjustment was completed.

Results

Identifying and describing burnout profiles

To answer RQ1 and RQ2, the optimum number of latent profiles and population share was investigated in each profile. Initially, 11 possible combinations of models, varying by number of classes and parameterisation, were tested (Table 3). Class Variant Unrestricted Parameterisation (CVUP; see Table 2 for an explanation of each model), with three profiles and two profiles, was further examined due to their lower AIC and BIC levels (with lower levels indicating a better fit). As seen in Table 4, CVUP 3 profiles showed lower AIC and higher entropy (entropy = 0.55), therefore it was selected as the optimum fit. Celeux and Soromenho (1996) suggested that standardised entropy values of 0.4–0.6 indicate low inter-profile heterogeneity. Nonetheless, even when entropy is close to 1, there can be a high degree of error in latent profile assignment, and more model uncertainty is added with more latent classes (Tullett-Prado et al., 2021). CVUP 3 was selected as the optimum solution because (i) CVUP 2 profiles showed lower entropy than CVUP 3, and (ii) CVUP 4 with four profiles did not converge on an adequate fit for the data.

The characteristics of the three profiles in CVUP 3 were investigated. The share of participants in each estimated profile was 33.8% for Profile 1 ($n = 153$), 28.0%) for Profile 2 ($n = 127$), and 38.2% for Profile 3 ($n = 173$). Table 5 displays each profile's standardised mean scores, raw mean scores, and standard deviations of PE, RA, and NF (see supplementary tables for the latent profiles' misclassification probability). As seen in Figure 1, Profile 1 comprised players who had low levels of PE (−0.92SD), RA (−0.86SD), and NF (−1.01SD), which were approximately one standard deviation below the mean. Consequently, Profile 1 was labelled Low Burnout Risk (LBR). Profile 2 comprised players who had moderate levels

Table 3. Initial model testing.

Model	Profiles	AIC	BIC	AWE	CLC	KIC
CIDP	2	7173.999	7215.158	7304.758	7155.557	7186.999
	3	7016.410	7074.032	7200.004	6990.061	7033.410
	4	6954.560	7028.646	7191.113	6920.179	6975.560
CVDP	2	7169.828	7223.335	7340.217	7145.453	7185.828
	3	7014.245	7096.563	7277.351	6975.775	7037.245
	4	6911.840	7022.969	7267.501	6859.437	6941.840
CIUP	2	6932.119	6985.626	7103.236	6907.016	6948.119
	3	6891.226	6961.196	7115.011	6858.381	6911.226
	4	6869.822	6956.256	7146.242	6829.270	6893.822
CVUP	2	**6848.042**	**6926.244**	**7098.691**	**6810.796**	**6870.042**
	3	**6838.917**	**6958.278**	**7221.542**	**6782.014**	**6870.917**
	4	N.C	N.C	N.C	N.C	N.C

This table shows comparisons between different numbers of profiles for four possible combinations of model parameters (including varying/fixed classes and varying/fixed covariances. Highlighted results (bold) indicate the best model parameterisation 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 CVUP with three profiles and two profiles.

Model	Profiles	AIC	BIC	Entropy	Proportion of smallest profile	BLRT-p
CVUP	2	6848.00	6926.00	0.377	0.406	0.00990
CVUP	3	6839.00	6958.00	**0.549**	0.280	0.0891

BLRT-p=Bootstrapped likelihood ratio test. This table shows that CVUP model with three latent profiles demonstrates a lower AIC and higher entropy value, resulting in better differentiation between profiles.

Table 5. Description of burnout profiles, including population share and raw and standardised mean scores of PE, RA, and NF.

Profile	N	%	RA	Z RA	PE	Z PE	NF	Z NF
1: Low Burnout Risk (LBR) class	153	33.8	10.90	−0.855	9.80	−0.921	9.60	−1.01
2: Medium Burnout Risk (MBR) class	127	28.0	14.40	0.0962	15.40	0.354	15.40	0.538
3: High Burnout Risk (HBR) class	173	38.2	16.50	0.686	16.20	0.555	15.30	0.500

Z scores represent standardised scores, and Standard deviation is presented between brackets.

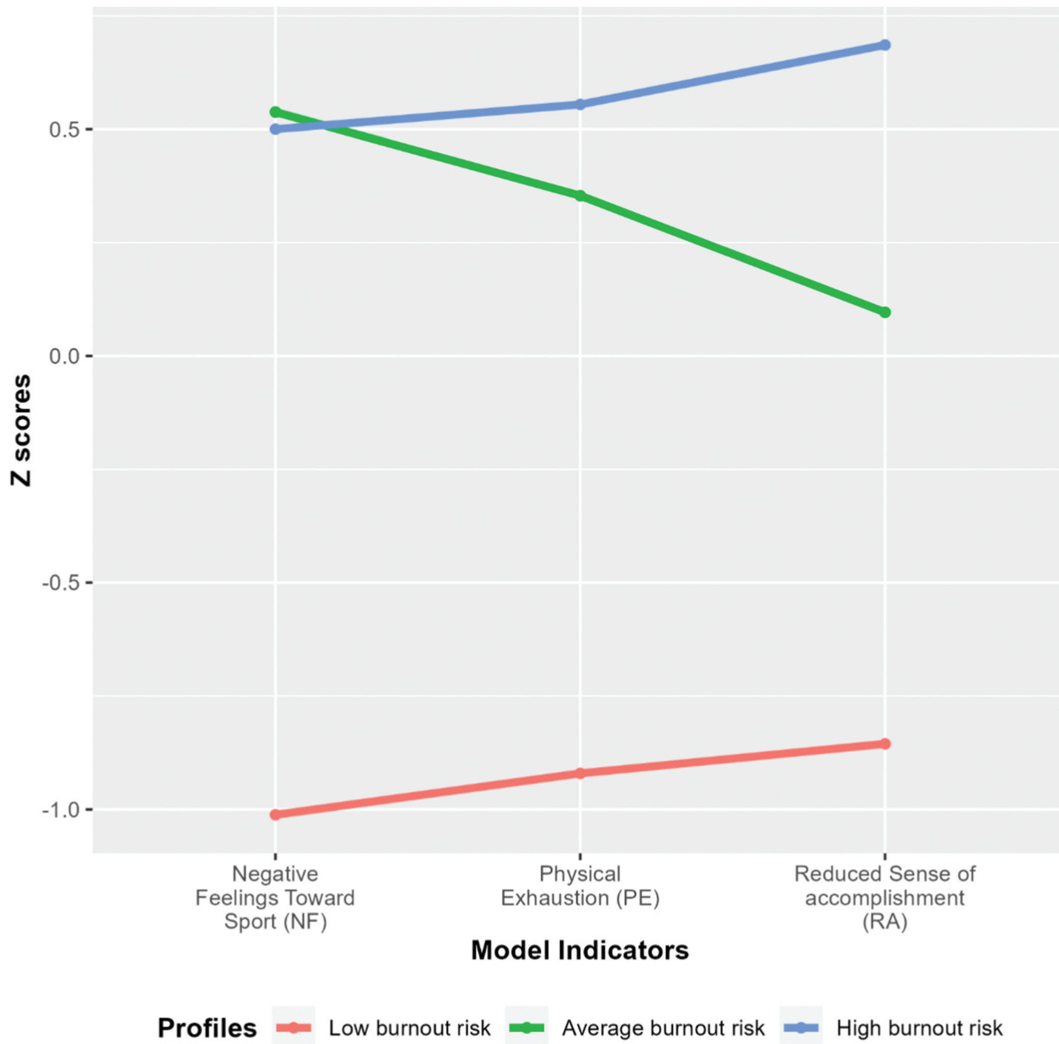

Figure 1. This plot illustrates three distinct latent profiles considering participants' symptoms of burnout assessed in standard deviation from the mean, including physical exhaustion, reduced sense of accomplishment, and negative feelings towards sport. The high line represents participants experiencing high levels of burnout, the middle line medium levels, and the lower line low levels.

of PE (0.35), average RA (0.09), and high levels of NF (0.54). Therefore, Profile 2 was labelled Medium Burnout Risk (MBR). Finally, Profile 3 comprised players who had half of a standard deviation above the mean or greater across PE (0.56), RA (0.69), and NF (0.50). Therefore, Profile 3 was labelled High Burnout Risk (HBR), and it was the most clearly distinguished from the MBR class (Profile 2) by players who reported high RA.

Mental toughness and resilience in burnout

Two separate one-way ANOVAs were conducted to examine the differences between mental toughness and resilience scores within Profile 1 (LBR), Profile 2 (MBR), and Profile 3 (HBR; see supplementary tables for assumption testing and misclassification errors). For mental toughness, the results indicated there was a significant difference between burnout profiles: F_{Welch} (2,146.5) = 31.30, $p < .001$, $\eta^2 = 0.122$. This showed a medium effect size ($\eta^2 = 0.01$ indicates a small effect, $\eta^2 = 0.06$ indicates a medium effect. $\eta^2 = 0.14$ indicates a large effect [Cohen, 2013]). Tukey's post hoc analysis shows that mental toughness scores in Profile 1 were significantly higher than Profile 2 ($p < .001$; SE = .99; CI = 0.41–0.89) and Profile 3 ($p < .001$; SE: .92; CI = 0.63–1.01). There were no difference in mental toughness between Profile 2 and 3. For resilience, the results showed that there was a significant difference between burnout profiles: F_{Welch} (430.8) = 10.8, $p < .001$, $\eta^2 = 0.046$ (showing a small effect size). Tukey's post hoc analysis showed that resilience scores were significantly higher in Profile 1 than in Profile 2 ($p < .002$; SE = .76; CI = 0.17–0.65) and Profile 3 ($p < .001$; SE = .70; CI = 0.27–0.71). There were no differences in resilience between Profiles 2 and 3.

Discussion

The present study is the first to use LPA to examine the relationship between burnout profiles, mental toughness, and resilience among esports athletes. This was done utilising psychometrically sound and widely utilised scales for assessing burnout, mental toughness, and resilience, along with a statistically advanced sequence of 24 potential profiling models. The study explored the number of burnout profiles among competitive esports athletes and identified three distinct profiles. Moreover, the three profiles were of roughly equal proportion. Finally, the results indicated that players who had higher levels of mental toughness and resilience reported lower levels of burnout.

Different burnout profiles among esports players

The findings suggested three distinct profiles of burnout present within this sample of esports players. These profiles comprised "Low Burnout Risk" (LBR; 33.8%), "Medium Burnout Risk" (MBR; 28.0%), and 'High Burnout Risk (HBR; 38.30%). The LBR profile was categorised by low scores across PE, RA, and NF. This finding suggests that players who experience low burnout report low burnout symptoms across all three variables. Players in the MBR and HBR classes reported similar scores on PE and NF but were clearly differentiated by RA scores. Players in the HBR class reported the highest levels of RA and total burnout. These findings show that players who experienced burnout symptoms were likely to experience PE and NF concurrently and that it is the experience of RA that differentiated between medium and high burnout risk. This suggests that players who experienced a reduced sense of accomplishment (RA) could be at the highest risk of experiencing severe burnout.

Traditional samples of sports athletes assessed with the ABO-S reported higher levels of PE, followed by RA and NF (Isoard-Gautheur et al., 2018). RA might be associated with higher burnout levels because it could precede PE and NF (Giusti et al., 2020). In a meta-analysis, Giusti et al. (2020), suggested that there might be a progression in the "order" in which athletes experience burnout symptoms, with RA, potentially acting as an early indicator. This suggests that athletes who feel they are not achieving their goals or not performing up to their standards may then start to experience more PE and NF. The results of the present study could indicate that similar to traditional sports athletes, esports players who experience RA may precede the experience of other burnout symptoms and be associated with higher levels of burnout risk. Using network analysis, Poulus et al. (2024) found that RA was highly influential, meaning it was strongly associated with other nodes in the network of resilience, coping, and burnout. The findings of the present study expand this knowledge and suggests that the influence of RA is a potential primary indicator among players who are at high burnout risk.

Future burnout research should investigate if RA uniquely predicts burnout among esports players, where PE is less likely due to the sedentary nature of esports. If RA is a primary indicator for esports burnout, this could have significant clinical and practical implications for identifying and treating burnout among esports players. The present study's findings also support previous research among gamers and demonstrate that esports players do not comprise a homogeneous group. More specifically, they comprise distinct profiles distinguished by unique characteristics (Kovacs et al., 2022).

The highest proportion of competitive gamers were categorised in the HBR class (38.2%), suggesting that a high proportion of competitive gamers experience PE, RA, and NF scores more than 0.5 standard deviations above the mean. This supports previous findings regarding burnout in esports (Smith et al., 2022) and suggests that burnout is emerging as a significant mental health risk in esports (Poulus et al., 2024). Whilst not directly comparable, an LPA of internet gaming disorder in video gamers found that around 14% of gamers fit into the profiles with the highest gaming disorder risk (Tullett-Prado et al., 2021). The highest proportion of esports players in the present study falls into the HBR class, and this could suggest that higher proportions of esports players could be at risk of mental ill health than video gamers.

Relationship between burnout profiles, mental toughness, and resilience

As predicted, players with higher levels of mental toughness and resilience reported lower levels of burnout. Higher mental toughness and resilience scores were associated with membership in the LBR class. These findings suggest that resilience, as it is currently conceptualised in traditional sports research (i.e., a factor that protects against the potential negative effects of stress and pressure; Fletcher & Sarkar, 2013), may have a similar role as a protective factor for mental health. More specifically, burnout is often caused by the chronic experience of stress or maladaptive attempts to cope with stress (Gustafsson et al., 2011). The finding here that higher levels of resilience (a factor that protects against stress) were associated with lower burnout levels is consistent with previous research (Wu et al., 2022). These findings also extend on the work of Poulus et al. (2024), who reported that resilience was generally associated with burnout. The results of the present study show how different resilience levels are associated with different burnout profiles. Moreover, considering the large amount of stress and coping research emerging on esports players (Leis et al., 2024; Poulus et al., 2021a), future research should continue exploring the potential role of resilience as a protective factor that may buffer against the experience of stress and burnout.

Mental toughness being associated with members of the LBR class builds on previous esports research (Poulus et al., 2020) that found mental toughness' association with performance and extends on these findings to show potential protection against adverse mental health outcomes among esports players. Similar to resilience, mental toughness is a factor that can support people to face challenges (i.e., stressors). However, an important conceptual distinction between resilience and mental toughness is that mental toughness is associated with performance in favourable situations and adverse situations (Gucciardi et al., 2008), whereas resilience is primarily associated with responses to adverse situations (Fletcher & Sarkar, 2013). Despite this conceptual difference, higher levels of mental toughness were also associated with lower levels of burnout. This suggests that both mental toughness and resilience, through protecting players against the adverse effects of stress, could influence esports player's experience of burnout symptoms. Combined, the results suggest that similar to traditional sports, mental toughness and resilience might be two factors which can influence protect against mental-ill health among esports players.

Limitations and future research

Despite being the first study to explore burnout among esports through LPA, it is not without limitations. The present study used a cross-sectional, predominantly male, English-speaking sample with self-report data. Therefore, longitudinal studies in clinical and more culturally and gender-diverse populations (Eddy et al., 2024) conducted with diverse methods of collection might (i) help to extrapolate the present findings to other populations, (ii) delineate causality, and (iii) better understand the multiple aspects of burnout. More specifically, future research could experimentally test burnout symptoms and personality factors to understand better the mechanisms that influence esports players' experience and management of burnout. Considering that esports are very popular in the People's Republic of China and the Republic of Korea, accurately measuring the prevalence of burnout in these countries is important. Esports players were sampled from seven major esports titles. Therefore, the study's findings do not capture differences in burnout profiles that might occur between esports. Future research could explore burnout profiles in a single esport title sample and across the full range of in-game ranks (i.e., 0–100%ile) to improve the applicability of the findings.

Despite the suboptimal entropy level observed in the model (i.e., $h = 0.55$), the latent profiles were clearly distinguishable, providing salient qualitative distinction across profiles. Also, the reliability score for MTQ-18 ($\alpha = 0.77$) was lower than the ABO-S ($\alpha = 0.90$) and CD-RISC 10 ($\alpha = 0.84$), and this should be considered when interpreting the findings regarding mental toughness. Nonetheless, considering the reported entropy value and mental toughness reliability, the results reported here should be interpreted cautiously, and future research is needed to replicate the findings. More specifically, future research should investigate further the differences in RA between esports players with HBR and MBR. There are limited interventions in esports (e.g., Poulus et al., 2023), and the present study's findings could inform future interventions. For example, considering that players' RA levels appear to indicate a higher risk of burnout, future interventions on player wellbeing could attempt to influence players' sense of accomplishment from their esports participation to protect against burnout. Finally, future research should investigate the influence of mental toughness and resilience on esports players' burnout further.

Conclusion

The findings showed three clear burnout risk profiles among esports players and suggest that a high proportion of esports players may be experiencing symptoms of burnout. The most prominent burnout profile was the HBR, which appears to be differentiated from MBR by high RA levels. Furthermore, stable personality factors like mental toughness and resilience appear to protect against burnout symptoms. Finally, these findings highlight the need for further research into burnout and mental ill-health in esports.

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