15 (2) (2026) 611-619
Journal of Physical Education, Sport, Health and Recreations
http://journal.unnes.ac.id/journals/peshr

Social Anxiety Typologies in Gamers A Latent Class Analysis Approach

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Keywords

Esports; Latent class analysis; Social anxiety

Abstract

Gaming and esports are becoming increasingly embedded in the daily lives of young people, yet the psychological experiences of gamers are still not fully understood. Social anxiety, for example, is often studied as if all players experience it in a similar way. Such assumptions may overlook important individual differences. Using a secondary dataset comprising 13,050 gamers, this study employs Latent Class Analysis (LCA) to identify hidden patterns of social anxiety based on responses to the Social Phobia Inventory (SPIN). Item scores were chotomized into binary values to facilitate categorical latent class modeling. Class partitions were compared using AIC, BIC, and entropy values. The analysis supports a five-class structure comprising the Minimal Anxiety, Performance Anxiety, Moderate Anxiety, Interaction Anxiety, and Severe Anxiety classes. The identified classes also differ in demographic composition and gaming behavior characteristics. Different response patterns emerged across these classes, particularly between performance-related fear and interaction-related discomfort, with additional differences observed in demographic characteristics and gaming behavior across all classes. this result suggest that social anxiety among gamers does not develop uniformly. Instead, different groups appear to experience anxiety in context-specific ways, which may require tailored psychological support rather than general intervention models within gaming and esports environments.

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p-ISSN 2460-724X
e-ISSN 2252-6773

INTRODUCTION

In the past decade, gaming and esports have not only grown as a form of entertainment, but have also created a new social space for young players (Alnemr et al., 2024; Kegelaers et al., 2025). In fact, esports is now recognized as a potential career path in professional sports, where young players see it as a platform for shaping their social identity and career aspirations (Pedraza-Ramirez et al., 2025; Prastijo et al., 2025; Solmaz et al., 2025). In recent years, as the popularity of gaming has grown, so has attention to the psychological aspects of gamers. One important aspect is anxiety, including social anxiety, which can affect the gaming experience and psychological well being of players (Smith et al., 2022). Social anxiety is characterized by excessive fear or anxiety in social situations or performances, such as fear of being judged when interacting or performing in front of others (APA, 2020). In the context of traditional sports, athletes' anxiety is often studied because it is considered to affect their performance (Machado et al., 2025) Several studies have found differences in anxiety levels based on the type of sport and the gender of the athlete, with fe athletes often reported to have a higher prevalence of anxiety (Alnemr et al., 2024), However, some have reported no significant differences between men and women in certain psychological characteristics related to social interaction in games (Kaczmarek & Drążkowski, 2025). Among gamers, the question arises whether intense involvement in games (including online games involving virtual social interaction) is related to a certain level of social anxiety (Solmaz et al., 2025).

Research on gaming and mental health has produced uneven conclusions. In some cases, intensive gaming appears linked to distress and social withdrawal. Other studies report something different entirely, with certain players showing relatively stable or even adaptive psychological functioning despite long gaming hours. This inconsistency raises the possibility that gamers do not respond to gaming experiences in the same way. Some players may use gaming as an escape or compensation for social anxiety in the real world (Chang et al., 2021; Wei et al., 2012). Sauter and Draschkow (2017). To understand this diversity, it is important to recognize the limitation of variable-centered approaches, which assume homogeneity across individuals. Therefore, a latent class analysis (LCA) approach is needed. Psychological symptoms rarely emerge in identical ways across all individuals. Some gamers may struggle mainly in competitive situations, whereas others experience discomfort during ordinary social interaction. LCA makes it possible to detect those hidden response patterns by grouping participants according to similarities in how they answer observed indicators., LCA identifies unobserved clusters of individuals who share similar response configurations across observed variables, thereby capturing heterogeneity in the population (Aonso-Diego et al., 2024; Lee & Lee, 2024). This approach is useful for identifying specific subtypes or typologies. For example, it has been used in studies of social anxiety to distinguish between performance only and generalized social anxiety subtypes in large epidemiological samples (Peyre et al., 2016). The LCA approach has been proven effective in identifying risk subgroups in complex psychosocial data, allowing for more targeted interventions to be designed (Lee & Lee, 2024; Lyrvall et al., 2024; Widhiarso & Hadjam, 2016).

In the context of increasing player engagement, this study attempts to fill the knowledge gap regarding the typology of social anxiety in the gaming community, which has often been viewed only in a linear manner (Aonso-Diego et al., 2024). Using the LCA approach on Social Phobia Inventory (SPIN) data from gamers, we identified how many classes of social anxiety profiles exist and the unique characteristics of each class, as LCA has been proven effective in distinguishing subtypes of anxiety disorders in both clinical and general populations (Peyre et al., 2016; Rizkia et al., 2024). In addition, this study also analyzes differences in demographic characteristics and gaming behavior (gender, age, gaming intensity, types of games played, etc.) between the social anxiety classes formed, given that these factors are often significant predictors in the mental health profile of gamers (Solmaz et al., 2025; Wei et al., 2012). By identifying distinct anxiety profiles among gamers, this study seeks to contribute to a more differentiated understanding of psychological risk in esports settings. The findings may also help inform intervention strategies that are adjusted to the specific characteristics of each subgroup rather than relying on generalized psychological support models (Aonso-Diego et al., 2024; Lee & Lee, 2024). To date, little empirical work has examined whether social anxiety among gamers forms distinct subtypes

when analyzed using a person-centered approach. Most existing studies rely on variable-centered methods that assume homogeneity across individuals, potentially masking meaningful heterogeneity in psychological experiences. Despite growing attention toward mental health in esports, relatively little is known about whether gamers experience social anxiety in qualitatively different ways. One possible explanation is that previous studies have relied too heavily on average-based approaches that compress diverse psychological
experiences into a single score. The present analysis attempts to identify whether distinct anxiety profiles emerge within gaming populations and how those profiles relate to demographic and gaming related characteristics, even though players experiences may differ substantially. Using SPIN data and LCA, this study aims to determine how many latent social anxiety profiles are present among gamers and to describe the characteristics of each profile. In addition, the study explores how these profiles may contribute to a more nuanced understanding of anxiety in gaming and esports settings, even though the psychological experiences of gamers show much more complex variations. Based on the 17 item Social Phobia Inventory (SPIN) (Connor et al., 2000; Lyrvall et al., 2024). In addition to determining the number and characteristics of latent classes of social anxiety, this study also analyzes differences in demographic characteristics and gaming behavior between the formed classes (Lee & Lee, 2024; Sauter & Draschkow, 2017). The findings of this study are expected to provide empirical contributions to the development of a more nuanced understanding of social anxiety in the context of gaming and esports, as well as to serve as a basis for more targeted and individual based psychological intervention approaches (Aonso-Diego et al., 2024; Pedraza-Ramirez et al., 2025).

METHODS

Design and Participants This study is a surveybased secondary analysis of game players using a large scale dataset compiled by Sauter and Draschkow (2017). The dataset used in this analysis contained a total of 13,464 respondents who met the eligibility criteria, predominantly (94.3%) aged between 18 and 63 years (M = 20.92; SD = 3.29). The original data was collected online through an anonymous online questionnaire distributed via an online gaming community platform (Sauter & Draschkow, 2017). Several responses were removed before analysis due to incomplete data, duplication, or inconsistencies across key variables. After this screening process, 13,050 participants remained in the final dataset.

Social anxiety was measured using the Social Phobia Inventory (SPIN), a self report inventory consisting of 17 items designed to measure symptoms of social phobia, covering three main domains: fear, avoidance, and physiological symptoms in social situations (Connor et al., 2000). Examples of items in this instrument include “I avoid talking to strangers” and “Speaking in public makes me very afraid.” The original responses to this instrument use a 5 point Likert scale, from 0 (“not at all”) to 4 (“Extremely”).

Table 1. SPIN questionnaire form

Instruments Social Phobia Inventory (SPIN)
I am afraid of people in authority.
I am bothered by blushing in front of people.
Parties and social events scare me.
I avoid talking to people I don’t know.
Being criticized scares me a lot.
I avoid doing things or speaking to people for fear of embarrassment
Sweating in front of people causes me distress.
I avoid going to parties.
I avoid activities in which I am the center of attention.
Talking to strangers scares me.
I avoid having to give speeches.
I would do anything to avoid being criticized.
Heart palpitations bother me when I am around people.
I am afraid of doing things when people might be watching.
Being embarrassed or looking stupid are among my worst fears.
I avoid speaking to anyone in authority.
Trembling or shaking in front of others is distressing to me.

In this dataset, the score for each SPIN item has been binarized into a categorical indicator to represent the presence/absence of significant symptoms (0 = no significant symptoms, 1 = symptoms present), and labeled bin_SPIN1 to bin_SPIN17 for the purposes of latent class analysis modeling (Widhiarso & Hadjam, 2016). The item binarization approach was used to facilitate latent class modeling on categorical data, as is common practice in categorical indicator-based latent class analysis. Earlier psychometric evaluations of the SPIN reported strong internal consistency across different samples, with Cronbach's alpha values ranging from .89 to .94 (Connor et al., 2000).

Table 2. Scale Likert

Score	Quantitative Analysis	Binarization Score	Quantitative Analysis
4	Extremely	1	Presence
3	Very Much	1	Presence
2	Somewhat	1	Presence
1	A Little Bit	0	Absence
0	Not At All	0	Absence

Latent Class Analysis Latent class analysis (LCA) was performed on 17 binary SPIN indicators to identify unobserved subgroups in the population. Unlike approaches that focus only on relationships between variables, LCA examines how individuals cluster together according to similar response tendencies. Through this approach, hidden subgroup patterns within a population can be identified more clearly.(Patnode et al., 2011) . The analysis was performed using jamovi software (version 2.7).

A number of models with 2 to 5 latent classes were compared sequentially to determine the solution that best fit the data. The selection of the best model was based on a combination of statistical criteria and substantive interpretability, which included: the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, as well as the likelihood ratio (G2) value to assess goodness of fit (Lee & Lee, 2024; Nylund et al., 2007). In addition, entropy values are used to evaluate classification accuracy, where values close to 1 indicate clear class separation (Lyrvall et al., 2024). Once the optimal model was determined, each respondent was assigned a posterior membership probability for each latent class. (Lyrvall et al., 2024). The analysis focused on class identification and descriptive comparison across groups.

RESULTS AND DISCUSSION

The characteristics of the sample, both overall and across latent classes, are presented in **Table 3.** Of the total 13,050 gamers, the vast majority were male (94.3%). The mean age of participants was 20.9 years (SD ≈ 3.3), with most respondents (87.5%) aged between 18 and 24 years. Gaming intensity was predominantly high, with 1.5% of participants playing less than 7 hours per week, 26.2% playing between 7–20 hours per week, and 71.5% playing more than 20 hours per week. In terms of playing style, most participants reported playing online (92.9%), while offline-only players accounted for a very small proportion (0.4%), and those playing both modes were negligible (0.03%); the remaining 6.7% fell into other categories. Regarding occupation, 69.2% of respondents were students, 30.5% were employed, and 0.3% belonged to other categories. In terms of education, approximately 23.9% had attained a bachelor's degree or higher, while the remainder were at the high school level or below. This distribution suggests that the sample is heavily dominated by highly engaged gamers, which may influence the observed psychological profiles, particularly in relation to exposure to social and competitive gaming environments.

Table 3. Sample characteristics by latent class (N = 12,432).

Characteristic	Class 1 (Performance)	Class 2 (Severe)	Class 3 (Minimal)	Class 4 (Interaction)	Class 5 (Moderate)
	18.3% (n = 2,270)	4.9% (n=609)	52.1% (n=6,472)	9.8% (n = 1,217)	15.0% (n = 1,864)
Male (%)	94.4	94.6	94.3	93.2	93.9
Age 18-24 years (%)	88.1	87	87.6	84.9	86.5
Age 25-29 years (%)	9.6	10.5	10.1	11.3	10.8
Age ≥ 30 years (%)	2.2	2.5	2.3	3.8	2.7
Gaming > 20 hours/week (%)	72	72.5	72	69.8	73.5
Playstyle: Offline (%)	0.5	0.3	0.3	0.2	0.4
Playstyle: Online (%)	92.5	92.3	93.4	93	92
Playstyle: Both (%)	0	0	0	0	0.1
Students/College Students (%)	69.9	72.6	69.4	67.4	67.6

The latent classes are labeled as follows: Perf. refers to Performance Anxiety; Severe is Severe Social Anxiety (comprehensive); Minimal represents Minimal Social Anxiety; Interact. is Social Interaction Anxiety; and Moderate refers to Moderate Social Anxiety (general). It should be noted that the total percentage of category characteristics may not reach exactly 100% due to decimal rounding and the existence of an additional category (Other) that is not included in this summary table.

This distribution suggests that the sample is heavily dominated by highly engaged gamers, which may influence the observed psychological profiles, particularly in relation to exposure to social and competitive gaming environments.

Table 3 also presents differences across latent classes. Class 3 represents the largest group, comprising approximately half of the sample (≈50%), and is characterized by a demographic composition similar to the overall sample, with a predominance of male participants (93.2–94.6%) and a high proportion of students (69.4%). In contrast, Class 2 (Severe Social Anxiety) is the smallest group (≈4.9%) and, although it shows a similarly high proportion of male participants (94.6%), it is distinguished by a high proportion of individuals with intensive gaming behavior, with 72.5% playing more than 20 hours per week. This pattern is consistent with previous findings indicating that gaming populations are not homogeneous but consist of distinct psychological subgroups (Aonso-Diego et al., 2024; Lee & Lee, 2024). The dominance of the minimal anxiety class suggests that most gamers are psychologically adaptive, while smaller subgroups exhibit specific vulnerability profiles.

Class 1 (Performance Anxiety) and Class 4 (Interaction Anxiety) are moderate in size (≈18.3% and ≈9.8%, respectively). Class 4, in particular, shows a relatively high proportion of participants with high gaming intensity (69.8% playing more than 20 hours per week). Meanwhile, Class 5 (Moderate Social Anxiety), which accounts for approximately 15.0% of the sample, serves as the reference class. Its demographic characteristics are generally similar to the overall sample distribution, for example, with 93.9% male participants and 73.5% reporting gaming intensity above 20 hours per week. Following the description of participant characteristics, Latent Class Analysis (LCA) was conducted to identify underlying subgroups of social anxiety within the sample.

The results of the Latent Class Analysis (LCA) indicate that the 5-class model provides the best fit for the data. This model shows the lowest values of Akaike Information Criterion (AIC = 149,089) and Bayesian Information Criterion (BIC = 150,171) compared to alternative models. In contrast, the 4-class model yields higher values (AIC = 150,117; BIC = 150,960), indicating a less optimal fit.

Furthermore, the likelihood ratio comparison suggests that increasing the number of classes improves model fit. The entropy value of the 5-class model (0.781) indicates a relatively good classification accuracy, suggesting that individuals are clearly assigned to their respective classes. This level of classification accuracy supports the interpretability of the identified latent classes and strengthens the validity of subsequent profile-based interpretations

Table 4. Fit Indices for Latent Class Models (N = 13,050)

Number of Classes	Entropy	AIC	BIC	G^2
2 classes	0.896	157,399	157,765	52,868
3 classes	0.829	152,074	152,678	47,478
4 classes	0.829	150,117	150,960	45,458
5 classes	0.781	149,089	150,171	44,366

Based on these criteria, the 5-class model was selected as the most appropriate representation of social anxiety typology among gamers. The fit indices for models with 2 to 5 classes are presented in **Table 4,** To evaluate the classification accuracy of the model, the entropy value was examined, which ranges from 0.0 to 1.0 (Lee & Lee, 2024). In this study, a minimum threshold of 0.70 was used to indicate an acceptable model. Consistent with cluster evaluation principles, values above 0.70 reflect classifications that are internally consistent and well-separated from other groups (Navarro-Lucena et al., 2024). Therefore, the entropy value of 0.781 obtained in the final model indicates a relatively high level of classification accuracy, suggesting that the identified latent classes are well-defined with minimal overlap while the comparison of AIC and BIC values is illustrated in Figure 1. This finding indicates that social anxiety among gamers is better conceptualized as a multidimensional construct consisting of distinct profiles, rather than as a single continuous variable. This supports the assumption that social anxiety is not a unidimensional construct, but consists of multiple latent profiles. These findings reinforce the argument that social anxiety should be conceptualized as a multidimensional construct rather than a single continuum, particularly in digital social environments such as gaming. This aligns with person-centered approaches in psychological research, which emphasize heterogeneity in behavioral and emotional patterns (Lyrvall et al., 2024).

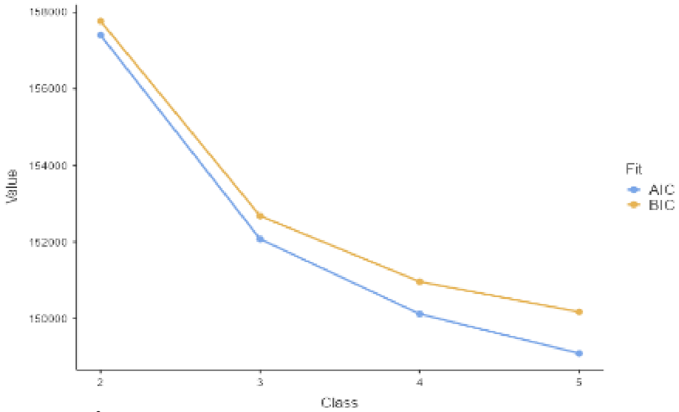

Figure 1. Elbow Plot for Latent Class Models

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Bold values indicate the best model fit indeks (minimum value) among the models tested. AIC and BIC elbow plots for LCA models with 2–5 classes. The curve flattens after 5 classes, supporting the selection of the 5-class model as a reasonable tolerance.

SPIN Item Response Patterns by Class

Each latent class exhibits a distinct response pattern across the 17 SPIN items. Figure 2 presents the probability of endorsement (“Yes”) for each item across the identified classes. A different pattern emerged in Class 2. Participants assigned to this group endorsed nearly all SPIN indicators at high probabilities, suggesting broad and persistent social anxiety symptoms across situations. In contrast, Class 3 (Minimal) demonstrates very low probabilities across all items, with values close to zero, suggesting an absence of significant social anxiety symptoms.

The remaining classes display more specific patterns. Class 1 (Performance Anxiety) is characterized by elevated probabilities on items related to public performance, while maintaining low probabilities on other indicators. For instance, items related to public speaking and being the center of attention show relatively higher endorsement, whereas items reflecting general social discomfort and physiological symptoms remain low. This pattern indicates that anxiety in this group is primarily situational and performance-related, consistent with the performance-only subtype of social anxiety (Peyre et al., 2016). This finding is consistent with clinical classifications of social anxiety that distinguish between performance-specific and generalized anxiety subtypes (Heimberg et al., 2014).

Conversely, Class 4 (Interaction Anxiety) demonstrates higher probabilities on items related to everyday social interactions, such as interacting with unfamiliar individuals or being observed by others, while showing relatively low probabilities on performance-related items. This suggests that individuals in this class experience anxiety primarily in informal social contexts rather than structured performance situations.

Class 5 (Moderate Anxiety) falls between the extremes, with moderate endorsement probabilities across a range of items (approximately 0.2–0.6). This indicates the presence of generalized but less severe social anxiety symptoms compared to the severe class.

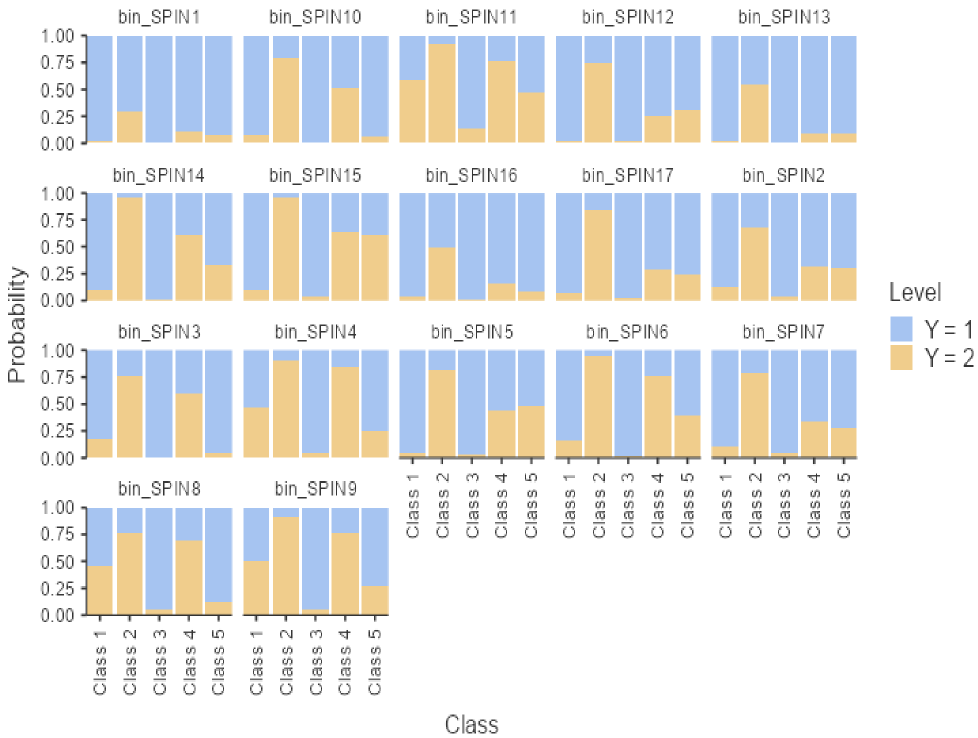

Figure 2. Depicts the item-response probabilities across the five classes, highlighting distinct symptom patterns.

Figure 2. Item response probabilities Y = 1 absence (blue), Y= 2 presence (yellow) for 17 SPIN items in each latent class. Class 2 (Severe) shows high endorsement probabilities across all items, while class 3 (Minimal) shows very low endorsement probabilities across all items. Class 1 (Performance) stands out as high on performance items (#9 center of attention, #11 speech) but low on other items; conversely, class 4 (Interaction) is high on interaction items (#4, #8, #14) but low on performance items. Class 5 (Moderate) is at an intermediate level on various items. The identified response patterns demonstrate that social anxiety among gamers is heterogeneous and consists of qualitatively distinct subtypes. This reinforces the importance of adopting a person-centered analytical approach in understanding psychological variability within gaming populations. The presence of these differentiated patterns in a gaming population suggests that virtual environments do not eliminate social anxiety, but rather reshape how it manifests across different situational contexts. These findings are consistent with prior latent class studies on social anxiety, which have identified distinct subtypes such as performance-specific and generalized anxiety profiles (Peyre et al., 2016).

Class Prevalence

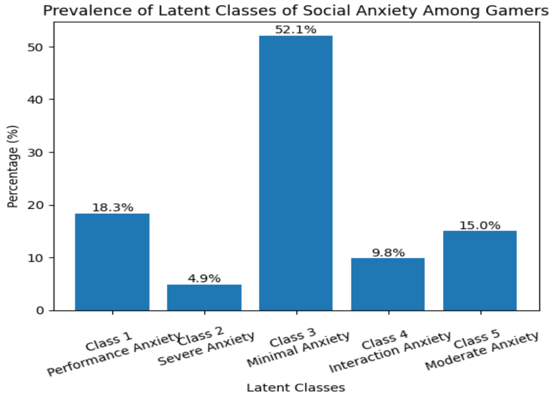

Figure 3. Prevalence of Latent Classes of Social Anxiety Among Gamers

The distribution of latent classes is presented in Figure 3. Class 3 (Minimal Social Anxiety) represents the largest proportion, accounting for 52.1% of the sample. In contrast, Class 2 (Severe Social Anxiety) constitutes the smallest group, comprising only 4.9% of participants.

The remaining classes fall within a moderate range: Class 1 (Performance Anxiety) accounts for 18.3%, Class 5 (Moderate Anxiety) for 15.0%, and Class 4 (Interaction Anxiety) for 9.8%. These findings indicate that the majority of gamers do not experience significant social anxiety, although a smaller subset exhibits moderate to severe symptoms. This contradicts common assumptions that gaming populations are uniformly at risk of psychological distress.

An important observation is the relatively large proportion of Class 1 (Performance Anxiety), which comprises nearly one-fifth of the sample. This pattern aligns with the DSM-5 "performance only" specifier in Social Anxiety Disorder, where individuals function well in general social contexts but experience anxiety in performance-related situations (APA, 2020). This suggests that performance-related anxiety is a distinct and relevant subtype within the gaming population. This finding highlights the importance of distinguishing between generalized and context-specific anxiety within gaming environments. In esports contexts, performance visibility and evaluation may intensify situational anxiety, even among individuals who otherwise function well in everyday social interactions (Machado et al., 2025; Pedraza-Ramirez et al., 2025).

Interestingly, performance-related anxiety appeared in a substantial portion of the sample despite relatively low indications of generalized social anxiety. One possible explanation is that competitive gaming environments place players under constant evaluation, making performance exposure psychologically demanding even for socially functional individuals.

CONCLUSION

Social anxiety among gamers appears far more varied than is often assumed. While many participants showed little indication of anxiety-related difficulties, several smaller groups displayed more situation-specific patterns tied either to performance pressure or interpersonal interaction. Interestingly, these classes did not simply differ in severity. They also differed in the kinds of situations that triggered distress. This pattern may help explain why previous research on gaming and mental health has often produced inconsistent conclusions. For practitioners working in esports or digital communities, a more individualized assessment approach may be more effective than relying on uniform intervention models.

REFERENCES

Alnemr, L., Salama, A. H., Abdelrazek, S., Alfakeer, H., Alkhateeb, M. A., & Torun, P. (2024). Prevalence of social anxiety disorder and its associated factors among foreign-born undergraduate students in Türkiye: A cross-sectional study. PLOS Global Public Health, 4(7), e0003184. https://doi.org/10.1371/journal.pgph.0003184

Aonso-Diego, G., González-Roz, A., Weidberg, S., & Secades-Villa, R. (2024). Depression, anxiety, and stress in young adult gamers and their relationship with addictive behaviors: A latent profile analysis. Journal of Affective Disorders, 366, 254–261. https://doi.org/10.1016/j.jad.2024.08.203

Chang, R. S., Lee, M., Im, J. J., Choi, K.-H., Kim, J., Chey, J., Shin, S.-H., & Ahn, W.-Y. (2021). Biopsychosocial factors of gaming disorder: A systematic review employing screening tools with well-defined psychometric properties. PsyArXiv. https://doi.org/10.31234/osf.io/b8fxr

Connor, K. M., Davidson, J. R. T., Churchill, L. E., Sherwood, A., Weisler, R. H., & Foa, E. (2000). Psychometric properties of the Social Phobia Inventory (SPIN): New self-rating scale. British Journal of Psychiatry, 176(4), 379–386. https://doi.org/10.1192/bjp.176.4.379

Heimberg, R. G., Hofmann, S. G., Liebowitz, M. R., Schneier, F. R., Smits, J. A. J., Stein, M. B., Hinton, D. E., & Craske, M. G. (2014). Social anxiety disorder in DSM-5. Depression and Anxiety, 31(6), 472–479. https://doi.org/10.1002/da.22231

Kaczmarek, L. D., & Drążkowski, D. (2025). Interpersonal capitalization in esports enhances players' psychological resources and well-being. Scientific Reports, 15(1), 32826. https://doi.org/10.1038/s41598-025-17968-1

Kegelaers, J., Mairesse, O., Van Ruysevelt, L., Trotter, M. G., Watson, M., Pedraza-Ramirez, I., Bonilla, I., Davis, P., Ragnarsson, J., & Van Heel, M. (2025). The mental health status of esports athletes. Journal of Electronic Gaming and Esports, 3(1), jege.2025-0017. https://doi.org/10.1123/jege.2025-0017

Lee, M.-S., & Lee, H. (2024). Latent class analysis of health behaviors, anxiety, and suicidal behaviors among Korean adolescents. Journal of Affective Disorders, 354, 339–346. https://doi.org/10.1016/j.jad.2024.03.025

Lyrvall, J., Bakk, Z., Oser, J., & Di Mari, R. (2024). Bias-adjusted three-step multilevel latent class modeling with covariates. Structural Equation Modeling: A Multidisciplinary Journal, 31(4), 592–603. https://doi.org/10.1080/10705511.2023.230008

Machado, S., Sant'Ana, L. D. O., Cid, L., Teixeira, D. S., Travassos, B., Monteiro, D., & Nardi, A. E. (2025). Effects of a playoff match on competitive anxiety and autonomic regulation in professional esports players. Clinical Practice & Epidemiology in Mental Health, 21(1), e17450179293069. https://doi.org/10.2174/0117450179293069250

Navarro-Lucena, F., Molinillo, S., & Anaya-Sánchez, R. (2024). Effects of the spectator's emotional attachment to esports players on the sponsoring brand. Academia Revista Latinoamericana de Administración, 37(4), 513–528. https://doi.org/10.1108/ARLA-05-2024-0094

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Structural Equation Modeling: A Multidisciplinary Journal, 14(4), 535–569. https://doi.org/10.1080/10705510701575396

Patnode, C. D., Lytle, L. A., Erickson, D. J., Sirard, J. R., Barr-Anderson, D. J., & Story, M. (2011). Physical activity and sedentary activity patterns among children and adolescents: A latent class analysis approach. Journal of Physical Activity and Health, 8(4), 457–467. https://doi.org/10.1123/jpah.8.4.457

Pedraza-Ramirez, I., Sharpe, B. T., Behnke, M., Toth, A. J., & Poulus, D. R. (2025). The psychology of esports: Trends, challenges, and future directions. Psychology of Sport and Exercise, 81, 102967. https://doi.org/10.1016/j.psychsport.2025.102967

Peyre, H., Hoertel, N., Rivollier, F., Landman, B., McMahon, K., Chevance, A., Lemogne, C., Delorme, R., Blanco, C., & Limosin, F. (2016). Latent class analysis of the feared situations of social anxiety disorder: A population-based study. Depression and Anxiety, 33(12), 1178–1187. https://doi.org/10.1002/da.22547

Prastijo, K. A.-T., Ali, M. A., Rahayu, T., Mega, G., & Abadi, J. C. (2025). Sponsorship in international sports events: A study of sponsors' perceptions of congruence, sincerity and brand exposure. Journal of Physical Education.

Publication manual of the American Psychological Association (7th ed.). (2020). American Psychological Association. https://doi.org/10.1037/0000165-000

Rizkia, A., Mar'at, S., & Suyasa, F. T. Y. S. (2024). Construct and criterion validation of social phobia inventory Indonesian version. Journal La Sociale, 5(3), 854–868.

Sauter, M., & Draschkow, D. (2017). Are gamers sad and isolated? A database about anxiety, life satisfaction and social phobia of over 13,000 participants. PsyArXiv. https://doi.org/10.31234/osf.io/mfajz

Smith, M., Sharpe, B., Arumuham, A., & Birch, P. (2022). Examining the predictors of mental ill health in esport competitors. Healthcare, 10(4). https://doi.org/10.3390/healthcare10040626

Solmaz, S., İnan, M., & Şahin, M. Y. (2025). The moderating effects of physical activity on social anxiety and sleep disturbance: Managing gaming disorder in young e-sports players. Frontiers in Public Health, 13, 1544044. https://doi.org/10.3389/fpubh.2025.1544044

Wei, H.-T., Chen, M.-H., Huang, P.-C., & Bai, Y.-M. (2012). The association between online gaming, social phobia, and depression: An internet survey. BMC Psychiatry, 12(1), 92. https://doi.org/10.1186/1471-244X-12-92

Widhiarso, W., & Hadjam, M. N. R. (2016). Aplikasi analisis kelas laten untuk mendeteksi karakteristik unik pada konstruk efikasi guru dalam mengajar. Jurnal Penelitian dan Evaluasi Pendidikan, 20(2), 244–254. https://doi.org/10.21831/pep.v20i2.769