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Psychotype and Thinking Style as Predictors of Success in Esports

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Abstract

Objectives. This study aimed to identify the cluster structure of esports athletes' psychological profiles based on psychotype, thinking style, age, and gaming experience, with the objective of applying the findings to training programs and psychological support.

Materials and methods. The study involved 53 esports players aged 18 to 27. Data were collected using psychodiagnostic tools: an adapted MBTI model, the Eysenck Personality Inventory (EPI), subjective scales for assessing emotional stability, and a thinking style questionnaire. Pearson's chi-square (χ^2) test for independent samples was used to compare observed and expected frequencies. Cluster analysis was conducted using the Statistica "Data Mining" module (k-means method, Euclidean distance, initial centers with maximum distance, and 10-fold cross-validation). ANOVA was applied to assess statistically significant differences in means within and between clusters. Bonferroni's post hoc test was used to determine which cluster pairs differed substantially. Hypotheses were tested at a significance level of $\alpha = 0.05$.

Results. Three clusters were identified based on psychotype: "Socially Adaptive" (32.1 %), "Introverted Analysts" (45.3 %), and "Active Extraverts" (22.6 %). Participants in the "Active Extraverts" cluster were older and had significantly more gaming experience. Two clusters emerged based on thinking style: "Structured Thinkers" (60.4 %) and "Adaptive Thinkers" (39.6 %), which differed considerably in their preference for clear instructions and planning strategies. The majority of players (over 85 %) demonstrated a logical or analytic-intuitive thinking style. A marked relationship was found between thinking style cluster affiliation and the overall score on the thinking style scale ($r_{p}b = 0.672$; $p < 0.0001$), confirming the validity of the clustering. The findings align with international data on cognitive flexibility, adaptability, and the role of mental coaching in esports.

Conclusions. The study proves that cluster analysis enables the typologization of esports athletes based on cognitive-behavioral profiles, thereby providing a foundation for the development of individualized training and psychological coaching programs.

Keywords: esports, psychotype, thinking style, cognitive profile, cluster analysis, psychological support.

Introduction

In modern esports, not only the players' technical skills play a significant role, but also their cognitive and psychological traits, which influence performance, stress resilience, and long-term professional engagement. Particular attention should be paid to the study of psychotypological characteristics and thinking styles, as well as their evolution with age and gaming experience. Despite the growing interest in esports as a professional field, there is a lack of systematic research focused on psychological player profiles using advanced statistical methods such as clustering (Martínent, Nicolas, et al., 2021; Torres Rodríguez, Griffiths, et al., 2018).

In Ukrainian academic discourse, there is a distinct shortage of in-depth empirical studies exploring esports athletes' psychological profiles through a comprehensive analysis of psychotype and cognitive style. Understanding these traits is essential for developing individualized training programs, preventing emotional burnout, assigning team roles, and increasing resistance to tournament stress (Bonnar, Gradisar, et al., 2024). It is especially important to track how these psychological and cognitive characteristics change based on the athlete's age and experience.

International research increasingly focuses on mental and cognitive mechanisms associated with success in esports. Himmelstein, Liu, and Shapiro (2017), emphasized the importance of mental skills—such as focus, emotional regulation, and self-control—for high-level performance. Pedraza-Ramirez et al. (2020) highlighted the lack of structured psychological research in esports and outlined priority areas, including cognitive control, temperament, and personality traits. Trotter et al. (2021) drew particular attention to the role of psychological support for players, justifying the need for applied sport psychology in esports for both individual development and team stability. Kegelaers et al. (2024) emphasize the importance of developing individualized mental health strategies that account for the cognitive and personality differences among players. In turn, Poulus et al. (2023) demonstrated that an esports-adapted cognitive-behavioral training program (E-CET) enhances stress resilience, subjective performance, and players' mental well-being. The study by Sanz-Fernández et al. (2025), conducted in traditional sports, shows the effectiveness of clustering and data mining methods for identifying psychotypological profiles, thus providing a solid foundation for implementing similar models in esports. Jang, Byon, et al. (2021) employed cluster analysis to segment players based on their level of engagement in esports. The 2025 study on FIFA player training indicates improvements in cognitive abilities (Imanian, Khatibi, et al., 2025).

Several Ukrainian studies also confirm the relevance of profiling esports players. In particular, the works of Shynkaruk et al. (2023, 2024) highlight the importance of psychological training, strategies to minimize tilt, and the adaptation of training programs to players' personality traits. Furthermore, Smith et al. (2019, 2022) draw attention to mental health risks among esports athletes, while Trotter et al. (2021,) emphasize the importance of psychological skills and social support as key success factors in competitive settings.

However, despite existing reviews and practical initiatives, there remains a lack of comprehensive empirical research that integrates psychotype, thinking style, gaming experience, and age using statistical clustering methods. This combination constitutes the scientific novelty of the present study, which aims to typologize the cognitive-behavioral profiles of esports athletes to enable more effective individualization of their preparation programs.

Despite the availability of general reviews, there is still a lack of studies combining cluster analysis with individual psychotypological traits of esports athletes—this constitutes the scientific novelty of this work.

The purpose of the study was to identify the cluster structure of esports athletes' psychological profiles based on psychotype, thinking style, age, and gaming experience, with the aim of applying the findings to training programs and psychological support.

Materials and Methods

Study participants

A total of 53 respondents (men and women aged 18–30) participated, all of whom had experience in official or semi-professional tournaments in such disciplines as Counter-Strike 2, Dota 2, Valorant, and League of Legends. The age range was 19–26 years, and gaming experience ranged from 3 to 10 years.

Study Organization

The research was conducted in 2025 among participants from the esports environment, particularly players.

This study employed a combination of empirical, mathematical-statistical, and psychodiagnostic methods, enabling an in-depth analysis of the psychological characteristics of esports athletes.

Surveying was used to collect primary data on age, experience, roles within the esports ecosystem, preferred disciplines, and self-assessment of psychological traits. A customized questionnaire adapted to the context of esports was utilized. Surveys and psychometric testing were conducted remotely and anonymously using a secured Google Forms platform.

Psychodiagnostics were employed to identify personality characteristics (psychotype), including a simplified version of the MBTI (Myers-Briggs Type Indicator) adapted for self-assessment, the EPI (Eysenck Personality Inventory) for evaluating extraversion/introversion and neuroticism, and subjective self-assessment scales for measuring emotional stability, reflection, and self-control. To examine thinking styles, a questionnaire was used that assesses the dominant mode of information processing (logical, analytical-intuitive, or intuitive). The questionnaire consisted of 25 closed and semi-open questions grouped into five thematic blocks: general information, psychotype, thinking style, temperament and stress response, and self-assessed emotional stability. The methodology was piloted on a sample of 30 esports athletes during a preliminary study.

Statistical Analysis

Prior to analysis, the normality of the distribution of quantitative data was verified using the Shapiro–Wilk W-test, appropriate given the sample size ($n = 53$). Since the distributions for age and experience did not conform to normality, the central tendency and spread were described using the first and third quartiles (Q1; Q3).

For comparing observed and expected frequencies, Pearson's chi-square test was applied. In the case of categorical data distributions, degrees of freedom (df) were calculated as the product of the number of categories minus one and the number of rows minus one (for contingency tables), or the number of categories minus one (for one-dimensional distributions) (Shynkaruk, Byshevets, et al. 2025).

Cluster analysis (k-means) was used to identify latent groups of esports athletes based on psychological characteristics. Cluster analysis, as an exploratory method, groups similar cases based on their shared characteristics without prior assumptions regarding the number or structure of the groups. To identify natural clusters in the data, the Data Mining module of Statistica software was used, specifically the k-means method with Euclidean distance as the metric and initial centers selected according to the maximum initial distance criterion.

To assess the stability of the results and minimize the risk of overfitting, 10-fold cross-validation was applied. In this approach, the dataset was randomly divided into 10 subsets with iterative training and testing of the clustering model.

The optimal number of clusters was determined automatically by the built-in mechanism of Statistica based on the training error minimization criterion.

As a result:

- Based on a set of psychological characteristics related to psychotype, three clusters were identified (training error: 0.9245);
- According to thinking style indicators, two clusters were formed (training error: 0.9129).

Pearson's chi-square test for independent samples was used to analyze independent distributions of qualitative variables (psychotype, community role, behavioral style, etc.).

Analysis of variance (ANOVA) was applied to determine statistically significant differences in mean values within and between clusters.

The F-test (Fisher's criterion) was used in ANOVA to determine whether statistically significant differences existed between mean values of two or more groups. This confirmed that the identified clusters differed significantly in terms of quantitative variables (experience, age). Degrees of freedom df1 (between groups) and df2 (within groups) were reported.

A scoring distribution method was also used as a confirmatory approach to categorize respondents based on total points.

Point-biserial correlation. To quantify the relationship between a dichotomous variable (cluster membership) and a continuous variable (e.g., scores, experience), point-biserial correlation was applied. This coefficient, a special case of Pearson's correlation, measures the strength and direction of association between group membership and scale values. In cases with more than two clusters, one-way ANOVA was used to identify statistically significant mean differences across clusters.

The Bonferroni post hoc test was employed to determine which cluster pairs differed significantly.

All hypotheses were tested at a significance level of $\alpha = 0.05$. Calculations were conducted using Statistica 10 (StatSoft, USA).

Data analysis was performed using the Statistica 10.0 software package (StatSoft, USA), in accordance with ethical standards of voluntary participation and confidentiality.

Results

The respondents' median age was 21.0 years (Q1 = 19.0; Q3 = 22.0), and their esports experience was 5.0 years (Q1 = 3.0; Q3 = 8.0), indicating that most participants entered the esports scene during adolescence.

A total of 53 individuals participated in the study, including players, coaches, and esports specialists. The study aimed to determine how different emotional states influence individual and team performance during preparation and competition across various esports disciplines.

An analysis of respondents' roles within the esports community showed that each participant typically identified with at least two roles (53 respondents gave 103 responses). Statistically significant preference was observed for the

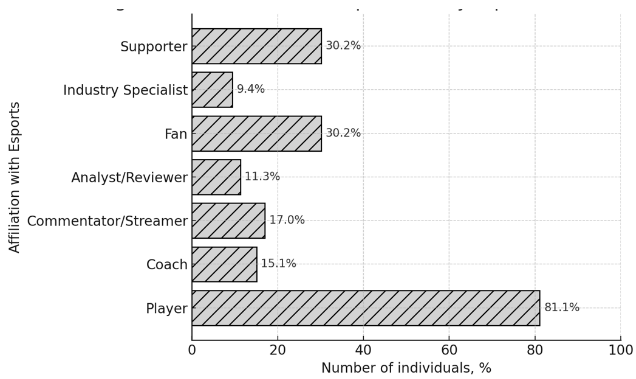

Fig. 1. Distribution of respondents by esports affiliation (n = 53)

player role, with 81.1 % identifying as players ($\chi^2 = 20.547$; df = 1; $p < 0.05$) (See Figure 1).

Respondents' answers about preferred esports disciplines varied greatly; however, 37.7% indicated either Counter-Strike 2 or Dota 2 as their main discipline.

To assess strengths and weaknesses in respondents' personalities, we applied a psychological assessment based on the MBTI model.

When analyzing psychotype data (extraversion vs. introversion), it was found that all parameters were statistically evenly distributed ($p > 0.05$), indicating no dominant tendency in the sample. This included comfort working in a team ($\chi2$=0.019; df=1; p=0.8907), preferred rest style (alone vs. in company) ($\chi2$=3.189; df=1; p=0.0742), reaction to social interaction (energized vs. fatigued) ($\chi2$=2.283; df=1; p=0.1308), decision-making style (reflective vs. impulsive) ($\chi2$=3.189; df=1; p=0.0742), and ease of making new acquaintances (easily vs. context-dependent or difficult) ($\chi2$=3.189; df=1; p=0.0742).

Cluster analysis showed that based on age (F=7.331; df1=2; df2=50; p=0.0016), experience (F=5.133; df1=2; df2=50; p=0.0094), and other psychological characteristics, the respondents could be grouped into three distinct clusters (See Table 1).

Cluster 1: "Socially Adaptive" (32.1%) – Respondents with a mean age of 19.1 years and 4.9 years of esports experience. They prefer group work, feel energized after social interaction, make considered decisions, enjoy social or event-based leisure, and form new connections situationally.

Cluster 2: "Introverted Analysts" (45.3%) – Mean age 22.1 years, 5.2 years of experience. Prefer solitude, feel fatigued after socializing, are reflective, prefer quiet rest, and tend to form connections based on context.

Cluster 3: "Active Extraverts" (22.6%) – Mean age 25.9 years, 9.8 years of experience. Enjoy teamwork, feel energized by social contact, act enthusiastically and impulsively, prefer social leisure, and make friends easily.

A clear link was established between psychotype, age, and experience. Members of Cluster 3 ("Active Extraverts") were statistically significantly older (25.9 years) and had longer gaming experience (9.8 years) compared to other groups.

This suggests that extraverted traits such as ease of forming connections and gaining energy from social interactions may contribute to greater longevity in esports careers.

Table 1. Characteristics of Esports Players by Cluster (n = 53)

Cluster	% of Sample	Mean Age (years)		Mean Experience (years)		Criterion	Chi-square / p value
		M	SD	M	SD		
Psychotype							
1. Socially Adaptive	32.1	19.1	2.8	4.9	2.6	Comfortable working in a group	χ^2=29.109; df=2; p<0.0001
						Effect of social interaction	χ^2=23.289; df=2; p<0.0001
2. Introverted Analysts	45.3	22.1	4.9	5.2	4.3	Thoughtful action	χ^2=12.792; df=2; p=0.0017
						Preferred rest	χ^2=16.260; df=2; p=0.0003
3. Active Extraverts	22.6	25.9	6.4	9.8	6.7	Ability to socialize	χ^2=27.894; df=4; p<0.0001
Thinking Style							
1. Structured Thinkers	60.4	20.9	3.9	4.7	3.4	Reliance on logic	χ^2=0.579; df=1; p=0.4469
						Trust in facts	χ^2=0.025; df=1; p=0.8737
						Need for instructions	χ^2=35.031; df=1; p<0.0001
2. Adaptive Thinkers	39.6	23.7	6.7	8.3	5.9	Adherence to plan	χ^2=23.049; df=1; p<0.0001
						Error analysis	χ^2=2.068; df=1; p=0.1504

Note. SD = Standard Deviation; M = Mean; df = degrees of freedom; Chi-square = chi-square test; p value = level of statistical significance (value "p < 0.0001" is shown as "<0.0001"; in other cases – rounded to four decimal places)

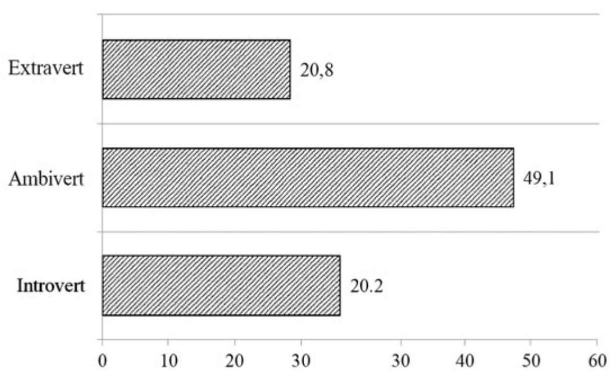

Fig. 2. Distribution of respondents by psychotype (n = 53)

Overall, cluster distribution among respondents was statistically even ($\chi2$=0.154; df=2; p=0.9259).

Additionally, using a scoring system for extraversion-related responses (1 point per extravert trait; total range 0–5), respondents were categorized as follows: 0–1 points = introvert, 2–3 = ambivert, 4–5 = extravert. Results showed that 49.1% were ambiverts, 30.2% introverts, and 20.8% extraverts (See Figure 2).

To verify whether the clusters aligned with extraversion-introversion scores, a one-way ANOVA was conducted. Statistically significant differences were found between clusters in terms of extraversion scores (F=66.07; df1=2; df2=50; p<0.0001). A post hoc Bonferroni test confirmed significant differences between all cluster pairs (p<0.0001), indicating clear differentiation among the groups.

The application of cluster analysis allowed us to identify three distinct psychotypological groups among esports athletes: "Socially Adaptive," "Introverted Analysts," and "Active Extraverts." An intriguing finding is that the "Active Extraverts" demonstrated significantly more gaming experience and were older on average. This may indicate that certain extraverted traits—such as ease of communication, impulsive and energetic actions, and deriving positive emotions from social interaction—are adaptive for a long-term career or extended presence in the esports environment, where teamwork and networking play a crucial role.

The consistency between the identified clusters and the scoring on the extraversion/introversion scale, as confirmed by one-way ANOVA ($F = 66.07$; $df_1 = 2$; $df_2 = 50$; $p < 0.0001$) and Bonferroni post hoc comparisons ($p < 0.0001$ for all pairwise comparisons), strengthens the reliability and validity of the psychotypological findings. This indicates that despite potential variability across specific traits, the clusters collectively form well-defined psychological profiles aligned with theoretical constructs of extraversion/introversion and merit further investigation.

In examining the thinking style of the respondents, we found that based on two criteria—namely, the tendency to rely on logic and facts when making decisions (as opposed to intuitive actions), and trust in analysis and evidence (compared to internal premonitions)—participants statistically significantly preferred a logical approach (in both cases, $\chi^2 = 6.811$; df = 1; p = 0.0091).

In contrast, for the responses to the questions "What suits you better?" (clear instructions / room for interpretation) and "Planning approach" (clear plan / spontaneity), the distribution of respondents did not differ significantly from uniformity ($\chi^2 = 0.472$; df = 1; p = 0.4922). However, esports athletes were statistically significantly more likely ($\chi^2 = 31.717$; df = 1; $p < 0.05$) to analyze their mistakes in order to avoid them in the future, rather than ignore them and move on.

Unlike the previous psychotype analysis, clustering based on thinking style criteria revealed two respondent groups that were less sharply defined in their characteristics.

Statistically significant differences between these clusters were observed only in the following indicators: gaming experience ($F = 7.798$; $df_1 = 1$; $df_2 = 51$; $p = 0.0073$), the need for clear instructions ($p < 0.05$), and planning approach ($p < 0.05$) (See Table 1).

Cluster 1: "Structured Thinkers" (60.4%). This group consisted of respondents with a mean age of 20.9 years and an average gaming experience of 4.7 years. They are characterized by a tendency to rely on logic and facts, trust in analysis and evidence, and a consistent practice of analyzing mistakes to prevent them in the future (these traits are shared across both clusters). At the same time, representatives of this cluster require clear instructions and follow a structured plan.

Cluster 2: "Adaptive Thinkers" (39.6%). This cluster included respondents with an average age of 23.7 years and a significantly greater gaming experience—8.3 years. Like the members of the first cluster, they rely on logic and facts, trust analysis and evidence, and analyze mistakes to avoid repeating them. A distinguishing feature of this group is their preference for interpretative freedom and their tendency to act spontaneously or creatively during planning.

A summary of the characteristics of the esports athlete clusters based on psychotype and thinking style is presented in Table 1.

Similar to the approach used for identifying the dominant psychotype, to determine the prevailing style of information processing, each response corresponding to the "logical" style was scored as 1 point. The total score ranged from 0 to 5 and allowed respondents to be categorized into three thinking styles: 0–1 point — intuitive; 2–3 points — analytical-intuitive; 4–5 points — logical. It was found that 45.3% of respondents demonstrate a logical thinking style, 41.5% — analytical-intuitive, and only 13.2% — intuitive (See Figure 3).

Since the point-based distribution of respondents by thinking style revealed three categories (logical, analytical-intuitive, and intuitive), whereas the cluster analysis identified two groups ("Structured Thinkers" and "Adaptive Thinkers"), an additional analysis was conducted to examine the relationship between these two approaches. The results of the point-biserial correlation calculation showed a statistically significant association between cluster

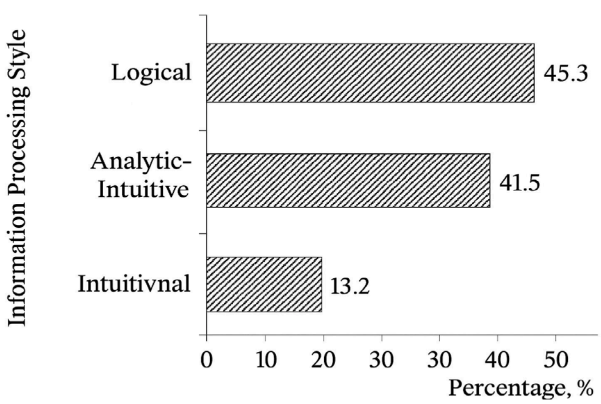

Fig. 3. Distribution of respondents by information processing style (n = 53)

membership and the total score on the thinking style scale ($r_pb = 0.672$; $t = 6.472$; $p < 0.0001$). This indicates that, despite the different number of identified categories, the clustering reflects substantial differences in cognitive profiles that are also measured by the point-based scale. Therefore, it can be concluded that the two clusters are clearly distinguishable based on the point-based measure, while the point-based distribution provides a more detailed classification (three categories).

The analysis of thinking styles among esports players revealed a complex picture of their cognitive processes. The score-based distribution showed a dominance of logical (45.3%) and analytical-intuitive (41.5%) thinking styles, with only a small proportion displaying an intuitive style (13.2%). This suggests that success in esports likely requires a high capacity for rational analysis, strategic planning, and processing large amounts of information.

Thus, the majority of esports athletes (over 85%) tend to exhibit either logical or balanced (analytical-intuitive) thinking styles. Pure intuitives represent a minority, which may indicate the importance of logic and analytical reasoning for success in esports—an environment where rapid data processing, situation assessment, and rational decision-making are essential.

In contrast, the exploratory cluster analysis, which empirically identified groups based on a combination of characteristics, revealed two distinct cognitive profiles: "Structured Thinkers" (60.4%) and "Adaptive Thinkers" (39.6%). Notably, these clusters differed statistically not in terms of basic logical or intuitive tendencies (as might be expected from direct correspondence to score-based categories), but in their need for clear instructions and planning approaches. "Structured Thinkers" showed greater dependence on external guidelines and clear action plans. This profile may be typical for players still actively mastering game mechanics and tactics, or for those who prefer relying on proven strategies.

In contrast, "Adaptive Thinkers," representing the minority, had significantly more gaming experience ($F = 7.798$; $df_1 = 1$; $df_2 = 51$; $p = 0.0073$) (8.3 years compared to 4.7 years for "Structured Thinkers"). This greater experience likely correlates with their lower reliance on detailed instructions and rigid planning. The findings suggest that they have developed cognitive flexibility and the ability to effectively adapt in dynamic and unpredictable gaming situations. Their experience likely allows them to rely on intuition and rapid decision-making beyond pre-planned strategies, enabling room for interpretation and spontaneous or creative actions.

Thus, the results highlight that while logical and analytical approaches dominate in esports, players are differentiated by the degree to which they rely on structure versus adaptability. Specifically, greater experience is associated with the development of a more adaptive thinking style, characterized by less need for instruction and greater inclination toward flexibility and creativity during gameplay.

It is worth noting that the relationship between empirically identified clusters and the a priori defined score-based categories is a key aspect of our research. For both psychotype and thinking style, the score-based approach does not contradict the cluster analysis results, confirming the validity of both methods in the context of esports athlete profiling. Moreover, in the case of thinking style, the score-based classification provided three categories (logical, analytical-intuitive, intuitive), offering more detailed differentiation than the two clusters. This suggests that the two approaches complement each other—providing both generalized profiles (clusters) and finer-grained distinctions (score-based categories)—which are essential for a comprehensive understanding of esports athletes' cognitive characteristics.

Discussion

The use of cluster analysis made it possible to identify three psychotypological groups ("Socially Adaptive", "Introverted Analysts", and "Active Extraverts") and two thinking styles ("Structured Thinkers" and "Adaptive Thinkers"), which statistically differ in age, experience, and a range of psychological characteristics. This confirms the integrative nature of psychotype and cognitive style in shaping esports players' competitive success. Such an approach allows psychotype and thinking style to be viewed not as isolated variables, but as interrelated behavioral-cognitive profiles that evolve with experience.

The obtained results are consistent with the study by Martínent et al. (2013), in which different affective states of athletes before competitions were identified through cluster analysis. Similar to their findings, we identified clusters with pronounced extraversion traits associated with longer experience in esports, higher social engagement, and a greater ability to adapt quickly in competitive environments.

Our data also complement the results of Torres-Rodríguez et al. (2018), who identified groups of gamers with varying levels of emotional stability and anxiety. However, unlike their clinically oriented approach, our study focuses on the resource-based components of personality—such as decision-making style, energy balance in social interaction, and preferences in cognitive information processing.

Particularly noteworthy is the discovered relationship between respondents' experience and their thinking style: members of the "Adaptive Thinkers" cluster had significantly more gaming experience compared to the "Structured Thinkers" (8.3 vs. 4.7 years). This aligns with the hypothesis by Domínguez-González et al. (2024) suggesting that greater gaming experience correlates with the development of flexible decision-making strategies and a preference for creative thinking over formal instruction. Similar conclusions were also drawn in the work of Martínez-Gallego et al. (2021), which found that athletes with a higher number of matches played exhibit reduced reliance on external structures of control.

He novelty of this study lies in the comprehensive integration of cluster analysis with a scoring-based approach to verify and refine typologies. This methodology enabled the validation of identified clusters through independent methods—particularly the alignment between the quantitative assessment of extraversion and its cluster-based categorization. This indicates a high degree of consistency between empirical observations and psychometric scales, which is rarely achieved in previous studies.

Moreover, our results are the first to provide a detailed account of esports athletes' cognitive-psychological profiles not only by individual parameters but through their complex constellation. This can be used for the individualization of training processes, mental coaching, and team building. Such findings hold practical value for professionals in esports psychology, coaches, and performance analysts.

Considering the identified clusters of psychotypes and thinking styles, it is advisable to implement individualized training and mental programs tailored to the characteristics of each group. For example:

"Structured Thinkers" require clearly defined goals, step-by-step strategies, and systematic feedback. Scenario-based analysis and pattern-based training would be effective for them.

"Adaptive Thinkers", on the other hand, may achieve better results under dynamic training conditions that involve creativity, improvisation, and decision-making under uncertainty.

Work with "Active Extraverts" should focus on developing resilience under conditions of team responsibility, while "Introverted Analysts" should be supported in building communication skills, reducing anxiety, and enhancing emotional regulation during competitions.

The findings complement current international research on psychological support and cognitive profiling in esports athletes. For instance, Kegelaers et al. (2024) emphasize the importance of mental health in esports and the need to consider individual differences in approaches to psychological support. This aligns with our identification of two thinking styles—"structured" and "adaptive"—which may require fundamentally different mental coaching strategies.

Poulus et al. (2023) demonstrated the effectiveness of adapted cognitive-behavioral training (E-CET), aimed at enhancing resilience and subjective effectiveness in esports players. Our results highlight the need for similar individualized training that takes into account players' cluster affiliation. For example, "active extraverts" may benefit more from socially oriented strategies, while "introverted analysts" may gain from tools for self-reflection and emotional self-regulation.

The experience of Sanz-Fernández et al. (2025) is also of particular importance - they applied data mining methods to construct psychological profiles of track and field athletes. Their findings confirmed the effectiveness of clustering for athlete typology based on psychophysiological parameters. Our study extends this approach to the field of esports, demonstrating that cognitive profiles and psychotypes, similar to those in traditional sports, can be classified and used as a basis for training design.

Additionally, the study by Zhu et al. (2020) showed that player experience significantly influences team effectiveness through the phenomenon of faultlines, which aligns with the advantages observed in adaptive thinkers who demonstrated longer competitive experience.

Himmelstein et al. (2017) argue that effective adaptation to dynamic game environments largely depends on the cognitive structure of thinking. Their recommendation for structured training programs for beginners is consistent with the characteristics of our "Structured Thinkers" cluster, who had the least gaming experience.

Summarizing the positions of Smith et al. (2022) regarding mental health factors in esports athletes and the conclusions of Trotter et al. (2021) on the role of social support, it can be argued that the thinking profiles and psychotypes identified in this study have potential applications in the development of national psychological support programs. In particular, taking into account the specific characteristics of each cluster may enhance the effectiveness of mental preparation, reduce the risks of emotional burnout, and support a stable esports career. In the study by De Las Heras et al. (2020), the significance of extraversion was emphasized in the context of esports teams, especially as a factor contributing to career longevity—this aligns with our observation of the "Active Extraverts" cluster, which included the oldest and most experienced players.

Additionally, Potard et al. (2019) identified four types of gamers based on psychotype, confirming the viability of clustering based on personality traits. Vega González Bueso et al. (2020) classified adolescents with internet addiction based on comorbid psychotypes, which parallels our approach to psychological grouping.

On the other hand, the study Timokhov, & Sergeev (2023); Zhang (2002) highlights the weak correlation between thinking style and performance in League of Legends (LoL). Meanwhile, Barnett & Coulson (2021), Poulus et al. (2022), Wang (2025) emphasize the advantages of cognitive flexibility and systematic practice as key predictors of long-term success.

Martončik et al. (2024) applied the deliberate-practice framework to measure predictors of long-term success among CSGO and LoL players, finding that age and non-deliberate engagement, rather than intentional practice, significantly predicted performance. Pishchik et al. (2019) compared cognitive profiles of student esports competitors and nonplayers, discovering that intensive gaming correlates with lower logical and critical thinking abilities. Roose & Doherty's (2024) special issue highlights shifts in esports psychology, emphasizing how evolving mental skills and team dynamics shape performance under competitive pressure. Complementing these findings, a meta-analysis by Pohlmeyer et al. (2023) synthesizes evidence showing esports experts outperform amateurs in spatial cognition and attention—but not necessarily other cognitive dimensions—supporting the profile-focused, multidimensional approach we advocate.

Thus, the obtained results not only reinforce previous findings regarding the role of cognitive and personality traits in sports performance, but also offer a new methodological model for their typology to be used in profiling and talent selection in esports.

Conclusions

The conducted study made it possible to identify clearly differentiated cognitive-psychological profiles of esports athletes, confirming the interrelationship between psychotype, thinking style, age, and gaming experience. Three psychotypological clusters were identified ("Socially Adaptive," "Introverted Analysts," and "Active Extraverts"), which significantly differ in terms of age, gaming experience, and social interaction. The "Active Extraverts" demonstrated the longest gaming experience, indicating a potential advantage of extraverted characteristics in sustaining long-term participation in esports.

Two thinking styles were also identified ("Structured Thinkers" and "Adaptive Thinkers"), showing statistically significant differences in gaming experience and problem-solving approaches. "Adaptive Thinkers," who had longer playing experience, exhibited greater flexibility and the ability to make creative decisions.

The use of cluster analysis combined with a scoring approach confirms the validity and practical relevance of the obtained profiles. This approach enables the more effective design of training and psychological programs that account for the individual characteristics of athletes.

Prospects for Future Research

Promising directions for future research include examining the correlation between the identified psychotypes and thinking styles with specific performance indicators and effectiveness across various esports disciplines.

Limitations

This study has certain limitations: the cross-sectional nature of the research does not allow for clear causal inferences between psychotype, thinking style, and success in esports.

Conflict of Interests

The authors state that there is no conflict of interests.

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Психотип і стиль мислення як предиктори успішності в кіберспорті

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 9 с., 1 табл., 3 рис., 33 джерела.

Мета. Виявити кластерну структуру психологічних профілів кіберспортсменів на основі психотипу, стилю мислення, віку та ігрового досвіду для подальшого використання в тренувальному процесі та психологічної підтримки.

Матеріали і методи. У дослідженні взяли участь 53 кіберспортсмени віком від 18 до 27 років. Для збору даних використано психодіагностичні методики: адаптовану модель MBTI, опитувальник Айзенка (EPI), суб'єктивні шкали оцінки емоційної стійкості, опитувальник стилів мислення. Для порівняння спостережуваних і очікуваних частот використовувався критерій Пірсона χ^2 (хі-квадрат) для незалежних вибірок. Кластеризація даних, виконана за допомогою модуля Statistica «Data Mining» (метод k-середніх, евклідова відстань, початкові центри з максимальною початковою відстанню, з використанням 10-кратної крос-валідації). Дисперсійний аналіз (ANOVA) використано для перевірки статистично значущих відмінностей між середніми показниками в межах і між кластерами. Для виявлення, які саме пари кластерів статистично значуще відрізняються, використовувався апостеріорний критерій Бонферроні. Гіпотези перевірено на рівні значущості $\alpha = 0{,}05$.

Результати. Ідентифіковано три кластери за психотипом: «соціально адаптивні» (32,1 %), «інтроверти-аналітики» (45,3 %) і «активні екстраверти» (22,6 %). Учасники з кластеру «активні екстраверти» виявилися старшими за віком і мали значно більший ігровий досвід. За стилем мислення сформовано два кластери: «структуровані мислителі» (60,4 %) та «адаптивні мислителі» (39,6 %), що статистично відрізнялися за потребою в чітких інструкціях і підходом до планування. Більшість гравців (понад 85 %) схиляються до логічного або аналітико-інтуїтивного стилю мислення. Встановлено значущий зв'язок між кластерною приналежністю та бальним показником стилю мислення ($r_pb = 0{,}672$; $p < 0{,}0001$), що підтверджує валідність кластеризації. Отримані результати узгоджуються з міжнародними даними про когнітивну гнучкість, адаптивність і роль ментального коучингу в кіберспорті.

Висновки. Кластерний аналіз дозволяє типологізувати кіберспортсменів за когнітивно-поведінковими профілями, що створює основу для побудови індивідуалізованих програм підготовки та психологічного тренування.

Ключові слова: кіберспорт, психотип, стиль мислення, когнітивний профіль, кластерний аналіз, психологічна підтримка.

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