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FEATURE ENGINEERING FOR ROLE ASSESSMENT IN COUNTER-STRIKE 2

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ABSTRACT

Background. The classification of in-game roles in team-based shooters, particularly Counter-Strike 2 (CS2), is an essential component of esports performance analytics. Existing approaches primarily rely on aggregate ratings or empirical assessments, which do not adequately capture the multidimensional structure of player behavior. As a result, there is a need to construct a behavioral feature space capable of reflecting role-specific differences and enabling reliable automated classification.

Materials and Methods. To construct the feature space, publicly available statistics and, when necessary, *.dem* files containing detailed logs of in-game events were utilized. The foundation consists of seven HLTV behavioral attributes, supplemented with metrics specific to the Terrorist (T) and Counter-Terrorist (CT) sides, as well as map-dependent indicators. The data were pre-cleaned, normalized, and structured at the player–map level. For the analysis, Principal Component Analysis (PCA) was applied, along with Analysis of Variance (ANOVA) to identify map-dependent features, and correlation analysis to examine relationships among behavioral metrics.

Results and Discussion. The results demonstrated that typical roles (entry-fragger, lurker, support, AWPer, anchor, and IGL) form distinct regions within the multidimensional feature space that cannot be reduced to a single numerical index. A set of features most influential for differentiating roles was identified, along with metrics that exhibit stable behavior regardless of map or side. The analysis based on grouping players revealed the absence of a universal player profile: strong performance in some metrics is accompanied by lower values in others, reflecting natural role specialization.

Conclusion. The proposed approach provides an informative representation of behavioral features and enables automated identification of player roles in CS2 without relying on aggregate rating systems. The constructed feature space has practical value for scouting, roster optimization, and match analysis, and can also be adapted for detecting smurfing or other forms of anomalous activity. The methodology demonstrates interdisciplinary potential and is promising for broader applications in behavioral analytics within online services.

Keywords: Counter-Strike 2; player role classification; behavioral features; HLTV attributes; ANOVA; correlation analysis.

INTRODUCTION

In modern esports, player roles in team-based shooters are critical for achieving highly competitive performance. Like traditional sports – where, for instance, midfielders in football are distinguished as defensive or attacking – esports disciplines exhibit functional differentiation of players based on their in-game responsibilities and behavioral patterns. In

Counter-Strike: Global Offensive (CS:GO) and Counter-Strike 2 (CS2), several typical roles are commonly distinguished: the entry-fragger, who creates space for the team; the lurker, who operates independently and controls flanks; the support and in-game leader (IGL), who coordinate team actions; the AWPer, specializing in sniper engagements; and the anchor, responsible for holding specific map positions [1].

The relevance of role classification stems from the increasing need for esports teams to conduct rapid and well-grounded selection of players for specific tactical tasks. As in football or basketball scouting, where identifying a player's specialization relies on statistical and behavioral analysis, esports requires the detection of behavioral patterns that reflect underlying in-game roles. Role recognition in CS2 can be viewed as a particular case of the broader problem of user identification based on behavioral features in online environments [2]. In this context, in-game actions (such as the number of opening kills, frequency of utility usage, or clutch effectiveness) function as behavioral indicators analogous to those used in other domains for user segmentation, action prediction, or anomaly detection [3, 4].

Prior studies have already demonstrated attempts at automated role classification, particularly in Dota 2, where supervised and unsupervised learning techniques have been used to group players by playstyle [5], [6]. Approaches based on clustering behavioral data have proven effective in identifying patterns of player interaction, both in team-based strategy games and in other videogame genres [7–9]. However, for first-person shooters (FPS), this problem remains underexplored despite its applied significance and substantial potential for scouting, roster construction, and training analytics. The distinct contribution of this work lies in constructing a multidimensional space of behavioral features for FPS titles using publicly available statistical sources (HLTV.org) and demonstrating the applicability of statistical methods (PCA, ANOVA, and correlation analysis) for role identification in CS2.

Importantly, the formation of multidimensional behavioral feature spaces has interdisciplinary relevance. Similar to how behavioral analytics methods are used in financial systems to detect fraudulent transactions, they can be applied in esports to identify dishonest behavior, such as smurfing or abnormal player activity [6, 8, 10]. Therefore, the study of roles in CS2 integrates applied value for esports teams with the broader potential of behavioral analytics, making this direction promising for advancing anomaly detection methods and the analysis of player behavior in online services.

It is worth noting that an in-depth analysis of behavioral patterns and their application to detecting anomalies and dishonest activity in the Counter-Strike series was conducted in our previous work [11]. That study showed that players' behavioral characteristics - such as decision-making tempo, aiming stability, and abnormal accuracy or reaction metrics - can serve as reliable indicators of both playstyle and potential deviations. This further emphasizes the behavioral nature of role classification and highlights its potential for CS2-specific identification tasks.

MATERIALS AND METHODS

The primary data sources for CS2 analysis include .dem files, which contain detailed information on in-game events, as well as publicly available statistical platforms such as Faceit and the specialized portal HLTV.org [12]. It is also important to highlight the Skybox.gg platform [13], which provides analysts with tools for detailed monitoring of professional players' positional behavior on both the Terrorist (T) and Counter-Terrorist (CT) sides. The spatial patterns captured by the system are used to determine and assign player roles.

This study focuses on players with official HLTV profiles, as these individuals exhibit stable behavioral patterns formed on the basis of a large number of recorded matches. Historically, during 2020–2023, HLTV relied on aggregate performance metrics Rating 1.0

and Rating 2.0, derived primarily from kills, deaths, kill-death ratios, and related statistical indicators. In 2024, however, the platform introduced an improved set of seven behavioral attributes that more comprehensively characterize a player's individual playstyle (**Fig. 1**): Firepower, Entrying, Trading, Opening, Clutching, Sniping, and Utility.

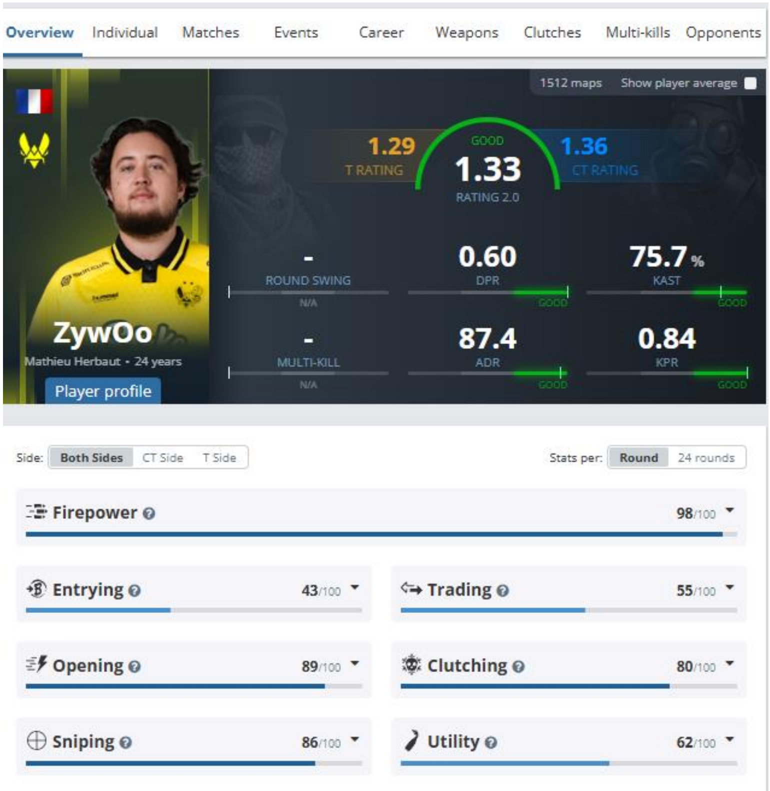

Fig. 1. Example of an HLTV profile of a professional player with the representation of their behavioral attributes.

Firepower – characterizes a player's individual effectiveness in combat. It includes the number of kills, the damage dealt, and multi-kills. High values indicate strong aimers and are often associated with key or “star” players.

Entrying – reflects how often a player dies during the first contacts with the opponent when entering a position held by the enemy. This metric is used to evaluate the effectiveness of entry fraggers who open the way for the team at the cost of personal risk.

Trading – shows how often a player is able to support the team by securing a kill immediately after a teammate dies. A high value means that the player effectively helps teammates during trades.

Opening – measures the frequency of successful first kills in a round. High values are typical of aggressive players (openers/entry fraggers) who create an early numerical advantage.

Clutching – reflects a player's ability to win rounds while being the last surviving member of the team against multiple opponents. This indicator shows individual skill, psychological stability, and strategic thinking.

Sniping – characterizes a player's performance with sniper weapons (AWP, Scout). It allows distinguishing pure snipers, hybrid players, and those who only occasionally use sniper rifles.

Utility – measures the frequency and effectiveness of using grenades (flashbangs, smokes, Molotov cocktails, HE grenades). High values of utility are typical of support players, who help create space and control the map for their teammates.

Sniper (AWPer) — high Sniping.

Entry fragger (aggressor/initiator) — high Opening and Firepower.

Lurker (flank/solo player) — low Trading combined with high Clutching.

Support — high Entrying and Utility, usually lower Firepower. Players who have high Trading are often called baiters (using teammates as bait).

To extract roles using machine-learning methods, a dataset was formed as a list of all players from the HLTV portal for role classification according to the roles described above. Since the features are behavioral, it is necessary to consider the different behaviors of a player on different game maps and in different teams.

Each entry in the dataset corresponds to a player–map pair and includes a multidimensional set of indicators that covers both general performance metrics (firepower, rating, damage per round) and behavioral characteristics related to game roles (entrying, trading, clutching, sniping, utility usage).

Indicators for the Terrorist and Counter-Terrorist sides are considered separately, which makes it possible to analyze the stability of roles in different game conditions and on different maps. The dataset also contains demographic variables (nickname, age) and map metadata, which makes it possible to account for the game environment context.

As a result, a dataset of 1464 observations was formed, covering 189 unique players who played on 8 competitive maps (de_ancient, de_anubis, de_dust2, de_inferno, de_mirage, de_nuke, de_train, de_vertigo). In total, the table contains 145 attributes, which underwent preprocessing to remove incomplete matches and z-score normalization to ensure the correctness of further analysis.

As shown in **Fig. 2**, no players exhibit simultaneously high values across all three metrics. This can be explained by the fact that trading and clutching represent opposing behavioral attributes: a player who operates alone cannot effectively participate in trade situations.

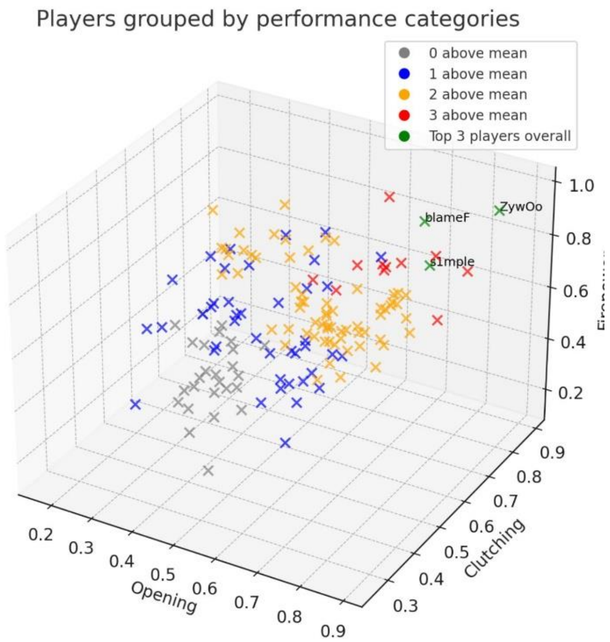

Fig. 2. Visualization of the firepower, clutching, and opening attributes.

Before conducting the analysis of variance, a preliminary data cleaning step was performed. Observations with missing values, as well as anomalous records resulting from parsing errors, were removed from the dataset. In particular, all cases in which any of the behavioral metrics (firepower, utility, trading, entrying, opening, clutching, sniping) exceeded the threshold value of 2.0 - substantially outside the typical [0;1] range - were excluded. After preprocessing, 1418 valid observations remained.

According to the results of the one-way ANOVA (see **Table 1**), with a significance level of $p < 0.05$, the metrics firepower ($F = 7.80$, $p = 2.72\times10^{-9}$), utility ($F = 77.72$, $p = 2.03\times10^{-95}$), trading ($F = 23.50$, $p = 2.36\times10^{-30}$), entrying ($F = 20.95$, $p = 5.75\times10^{-27}$), and clutching ($F = 3.16$, $p = 0.0026$) exhibit statistically significant differences across maps. In contrast, the opening ($p = 0.505$) and sniping ($p = 0.55$) metrics did not show significant differences, indicating that these parameters of playstyle remain relatively stable regardless of the map.

Table 1. **Results of the one-way analysis of variance**

Feature	F-value	p-value	Significance (p < 0.05)
firepower	7.80	2.72×10^{-9}	Yes
utility	77.72	2.03×10^{-95}	Yes
trading	23.50	2.36×10^{-30}	Yes
entrying	20.95	5.75×10^{-27}	Yes
opening	0.90	0.505	No
clutching	3.16	0.00256	Yes
sniping	0.84	0.550	No

During the correlation analysis, the following relationships between the behavioral features were identified (see **Table 2**), excluding the duplicated T/CT-specific metrics. The overall structure of inter-feature relationships is additionally presented in the form of a correlation matrix (**Fig. 3**).

Table 2. **Pearson correlation analysis results**

№	A pair of features	Cross-correlation coefficient, R
1	clutching – last_alive_percentage	0.726
2	firepower – opening	0.599
3	sniping – last_alive_percentage	0.556
4	entrying – last_alive_percentage	0.507
5	sniping – entrying	0.447
6	sniping – clutching	0.445
7	clutching – trading	0.294
8	entrying – clutching	0.291
9	entrying – trading	0.269
10	trading – last_alive_percentage	0.251

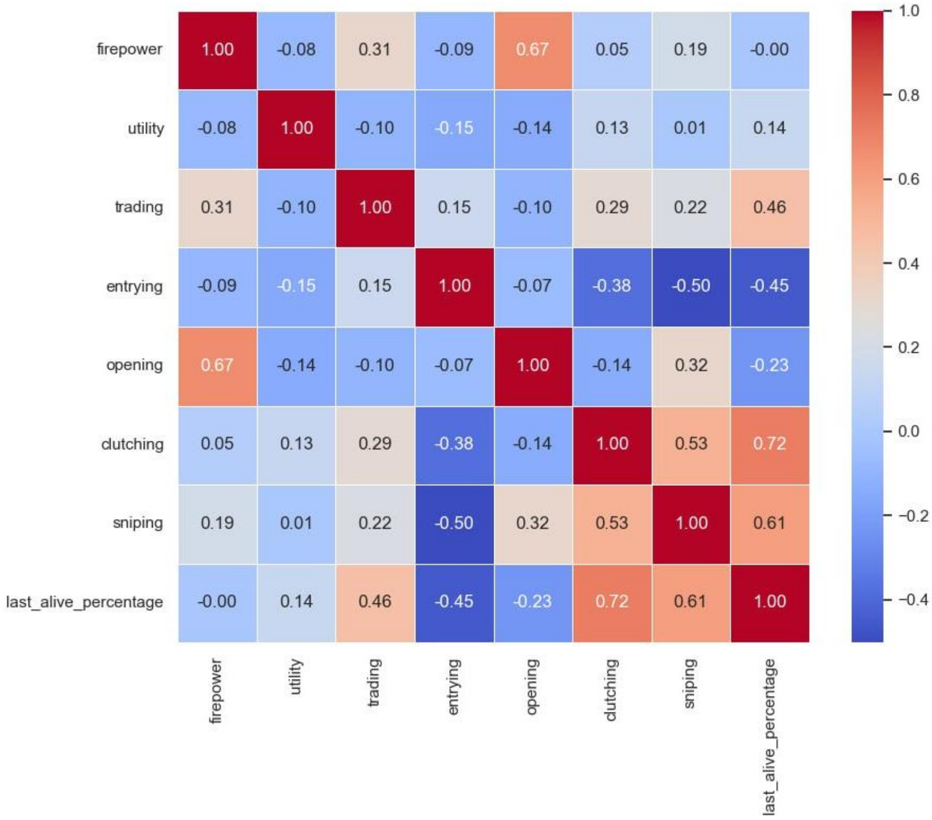

Fig. 3. Correlation matrix of key features.

RESULTS AND DISCUSSION

The conducted analysis showed that constructing a multidimensional space of behavioral features enables effective identification of player roles in CS2. The grouping of players based on their behavioral features demonstrated that even among top-tier players there is no universal "ideal" profile with high values across all metrics. For example, players with high firepower and clutching scores tend to exhibit lower trading values, which reflects the trade-off between individual playstyle and team-based trading during a round.

In contrast to the work in [4], which focused on verifying player identity using a Binary Random Forest model, the approach proposed in this study aims to classify functional roles based on interpretable HLTV behavioral attributes. A similar principle of using interpretable performance indicators for behavioral profiling was adopted in prior work on smurf detection in Dota 2, where clustering-based analysis relied on statistically meaningful in-game features rather than opaque model outputs [10]. By combining PCA, ANOVA, and correlation analysis, the study provides a multidimensional understanding of gameplay behavior that has both scientific and practical value for esports scouting, match analysis, and the detection of atypical players.

Building on the approach described in [4], where the sniper role was identified based on the frequency of weapon usage, the analysis showed that the sniping metric exhibits map independence and is sufficiently informative for unambiguous recognition of players in this role. In contrast, classification of other roles requires more complex features, as their behavior shows much higher variability depending on the map context.

ANOVA revealed statistically significant differences in several attributes depending on the map, confirming that gameplay context influences how roles manifest. This is particularly important for modeling, since a player's role may appear differently under various conditions, such as maps with narrow corridors versus open spaces. A similar conclusion regarding the importance of contextualized role modeling was reported by Demediuk et al. [6], who showed that role-aware analysis is essential for accurate interpretation of player behavior in Dota 2.

The correlation analysis revealed a set of meaningful interdependencies among the examined attributes, excluding duplicated T/CT metrics. These findings outline the underlying structure of how the behavioral indicators relate to one another. Players who frequently remain the last alive tend to have high clutching values, since clutching reflects the ability to win a round when being the last surviving player against multiple opponents. Firepower correlates strongly with opening, meaning strong aimers are more likely to secure opening duels. Sniping shows notable relationships with last_alive_percentage, entrying, and clutching.

The correlation analysis confirmed a number of patterns that are intuitive to players and analysts. Specifically, players who often remain last alive have high clutching values, and firepower correlates with opening, supporting the role of strong aimers as early duel initiators. Sniping was also connected with last_alive_percentage and entrying, indicating that sniper roles vary between aggressive and conservative playstyles.

The findings show that the highest values in individual metrics do not indicate a universal player, but instead reflect distinct behavioral specializations. This confirms that behavioral features can serve as a reliable tool for role identification, scouting, and assessment of individual player profiles. In addition, the constructed feature space has potential for detecting anomalous behavior, including smurfing or unusual activity patterns, which parallels fraud detection tasks in financial systems.

The conducted analysis showed that constructing a multidimensional space of behavioral features enables effective identification of player roles in CS2. This result is consistent with earlier studies on role classification in team-based competitive games, where multidimensional behavioral representations were shown to be essential for distinguishing functional player roles [5].

Several players demonstrated role changes when transitioning between teams, which affected their individual performance in different ways. Another factor is the transition from CS:GO to CS2, which also involved adaptation of roles and changes in playstyle. Moreover, some top players experimented with roles atypical for them. These aspects should be taken into account in future research.

CONCLUSION

The results of this study demonstrate that player roles in CS2 can be effectively identified using behavioral features extracted from publicly available statistical sources, particularly HLTV.org. By integrating HLTV attributes with PCA, ANOVA, and correlation analysis, the proposed approach reveals clear and consistent patterns corresponding to distinct in-game functional roles.

The analysis shows that specific combinations of behavioral indicators are strongly associated with particular roles. In particular, high firepower and opening metrics characterize entry fraggers; elevated utility and entrying values are typical of support players; sniping is a defining feature of AWPers; and the combination of high clutching with low trading reflects the lurker playstyle. While similar analytical frameworks have been applied in prior studies of player behavior and role classification [2], [3], the present results provide a role-specific and interpretable characterization tailored to CS2 using publicly accessible data.

The analysis showed that high performance in CS2 is not associated with uniformly high values across all behavioral attributes. Instead, players tend to exhibit differentiated profiles of strengths, where certain features dominate depending on the role. This indicates that each role is characterized by a specific combination of behavioral indicators rather than by overall performance across all metrics.

The observed player groupings and correlation patterns confirm the presence of stable behavioral structures within the data. In addition, the ANOVA results demonstrate that several performance-related attributes are map-dependent, indicating that player performance and the effectiveness of specific roles vary across different gameplay environments. This highlights the importance of accounting for contextual factors when modeling player roles and behavioral patterns.

The study shows that the constructed feature space can be used for player scouting, role-based selection, match analysis, and the optimization of training processes. The model can also help detect atypical or dishonest behavior, such as smurfing, which is consistent with existing approaches to anomaly detection and behavioral profiling [14]. More broadly, the results support current research on esports performance, highlighting the role of stable behavioral patterns and individual differences [15]. Overall, the proposed approach is relevant not only for esports analytics but also for behavioral monitoring and anomaly detection in other online systems.

Future work should explicitly examine differences between CS:GO and CS2, as changes in game mechanics, map design, and the underlying engine may affect the expression and stability of behavioral features and player roles across versions.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any.

AUTHOR CONTRIBUTIONS

Conceptualization, [Y.K., Yu.F.]; methodology, [Y.K., Yu.F.]; validation, [Y.K., Yu.F.]; writing – original draft preparation, [Y.K.]; writing – review and editing, [Y.K., Yu.F.]; supervision, [Yu.F.].

All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] Serafico, L. (2025, May 12). *Counter-Strike roles explained (and who does them best)*. *Esports Insider*. https://esportsinsider.com/counter-strike-roles-explained

[2] The utility of behavioral biometrics in user authentication and demographic characteristic detection: a scoping review. Syst Rev 13, 61. https://doi.org/10.1186/s13643-024-02451-1

[3] Seif El-Nasr, M., Drachen, A., & Canossa, A. (Eds.). (2013). Game Analytics: Maximizing the Value of Player Data. Springer. https://doi.org/10.1007/978-1-4471-4769-5

[4] Zimmer, F. (2025). Player behavior analysis for predicting player identity within pairs in esports tournaments: A case study of Counter-Strike using binary random forest classifier. Proceedings of the 58th Hawaii International Conference on System Sciences (HICSS 2025). University of Hawaiʻi at Mānoa. https://doi.org/10.24251/HICSS.2025.513

[5] Eggert, C., Herrlich, M., Smeddinck, J., Malaka, R. (2015). Classification of Player Roles in the Team-Based Multi-player Game Dota 2. In: Chorianopoulos, K., Divitini,

M., Baalsrud Hauge, J., Jaccheri, L., Malaka, R. (eds) Entertainment Computing - ICEC 2015. ICEC 2015. Lecture Notes in Computer Science(), vol 9353. Springer, Cham. https://doi.org/10.1007/978-3-319-24589-8_9

[6] Demediuk, S., York, P., Drachen, A., Walker, J. A., & Block, F. (2019). Role Identification for Accurate Analysis in Dota 2. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, *15*(1), 130-138. https://doi.org/10.1609/aiide.v15i1.5235

[7] Drachen, A., Sifa, R., Bauckhage, C., & Thurau, C. (2012). Guns, swords and data: Clustering of player behavior in computer games in the wild. Proceedings of the IEEE Conference on Computational Intelligence and Games (CIG 2012) (pp. 163–170). IEEE. http://doi.org/10.1109/CIG.2012.6374152

[8] C. Bauckhage, A. Drachen and R. Sifa, "Clustering Game Behavior Data," in IEEE Transactions on Computational Intelligence and AI in Games, vol. 7, no. 3, pp. 266-278, Sept. 2015, doi: https://doi.org/10.1109/TCIAIG.2014.2376982

[9] Ferguson, M., Devlin, S., Kudenko, D., & Walker, J. (2020). *Player style clustering without game variables*. In Proceedings of the IEEE Conference on Games (CoG 2020) (pp. 556–563). IEEE. https://doi.org/10.1145/3402942.3402960

[10] Ding, Y.-J., Yap, W.-S., & Khor, K.-C. (2024). Profiling and identifying smurfs or boosters on Dota 2 using K-means and IQR. IEEE Transactions on Games. https://doi.org/10.1109/TG.2023.3317053

[11] Kuzhii, Y., & Furgala, Y. (2024). The anticheat development in the Counter-Strike main series. Electronics and Information Technologies, 26, 88–97. https://doi.org/10.30970/eli.26.8

[12] HLTV.org. (2024). Introducing HLTV Attributes. Retrieved from https://www.hltv.org

[13] Skybox Technologies ApS. (n.d.). *CS2 stats – Track your stats like the pros | Skybox EDGE*. Skybox EDGE. https://skybox.gg/edge/

[14] Qian, X., Sifa, R., Liu, X., Ganguly, S., et al. (2022). Anomaly detection in player performances in MOBA games. In Proceedings of the Australasian Computer Science Week (ACSW) 2022. ACM. https://doi.org/10.1145/3511616.3513095

[15] 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 & Exercise, 81, 102967. https://doi.org/10.1016/j.psychsport.2025.102967

ФОРМУВАННЯ ПРОСТОРУ ОЗНАК ДЛЯ ОЦІНЮВАННЯ РОЛЕЙ У COUNTER-STRIKE 2

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АНОТАЦІЯ

Вступ. Класифікація ігрових ролей у командних шутерах, зокрема у Counter-Strike 2 (CS2), є важливою складовою аналітики кіберспортивної продуктивності. Існуючі підходи здебільшого спираються на інтегральні рейтинги або емпіричні оцінки, що не дає змоги повноцінно врахувати багатовимірну структуру поведінки гравців. Унаслідок цього виникає потреба у формуванні простору поведінкових ознак, здатного відображати відмінності між ролями й забезпечувати коректну автоматизовану класифікацію.

Матеріали та методи. Для побудови простору ознак використано відкриту статистику та, за потреби, .dem-файли з деталізованими журналами ігрових подій. Основу становлять сім поведінкових атрибутів HLTV, доповнених показниками для сторін терористів (T) і контртерористів (CT), а також метриками, чутливими до конкретних карт. Дані попередньо очищено, нормалізовано та структуровано на рівні гравець–карта. Для аналізу застосовано метод головних компонент (PCA), дисперсійний аналіз (ANOVA — Analysis of Variance) для виявлення картозалежних ознак та кореляційний аналіз для оцінки зв'язків між поведінковими метриками.

Результати. Результати показали, що типові ролі (entry-fragger, lurker, support, AWPer, anchor, IGL) формують окремі області у багатовимірному просторі, які не зводяться до єдиного числового індексу. Виявлено набір ознак, що найбільше впливають на розмежування ролей, а також показники зі стабільною поведінкою незалежно від карти чи сторони. Кластеризація виявила відсутність універсального профілю гравця: сильні показники в одних метриках супроводжуються нижчими значеннями в інших, що відображає природну рольову спеціалізацію.

Висновки. Запропонований підхід забезпечує інформативне представлення поведінкових ознак і дозволяє автоматично ідентифікувати ролі гравців у CS2 без використання інтегральних рейтингів. Сформований простір ознак має прикладну цінність у скаутингу, підборі складів і аналізі матчів, а також може бути адаптований для виявлення смурфінгу чи аномальної активності. Методика демонструє міждисциплінарний потенціал та перспективність для ширших задач поведінкової аналітики в онлайн-сервісах.

Ключові слова: Counter-Strike 2; класифікація ролей гравців; поведінкові ознаки; HLTV attributes; ANOVA; кореляційний аналіз.

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