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ORIGINAL

Under the Radar: Quantifying the Tactical Influence of Support Roles in Competitive Dota 2 Using Open Match Telemetry and Deep Learning

Bajo el Radar: Cuantificación de la Influencia Táctica de los Roles de Apoyo en Dota 2 Competitivo Usando Telemetría Abierta y Aprendizaje Profundo

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ABSTRACT

In the competitive realm of Multiplayer Online Battle Arena (MOBA) games like Dota 2, support roles are often undervalued despite their strategic importance in determining match outcomes. Traditional metrics emphasize kills, gold accumulation, and damage output, which inadequately capture the tactical influence of support players. This study employs a deep learning approach—combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and XGBoost—to analyze a large-scale dataset from OpenDota comprising over 20 000 competitive matches. By leveraging match telemetry and spatio-temporal data, the proposed model quantifies support player impact using explainable AI (XAI) techniques such as SHAP. The results reveal distinct behavioral patterns and contributions of support roles in vision control, teamfight initiation, and strategic movement, offering a new lens for talent identification and coaching. This work contributes to the development of performance evaluation frameworks that holistically represent the complexity of team-based esports.

Keywords: Dota 2; Support Roles; Game Telemetry; Deep Learning; E-Sports Analytics; Performance Prediction; Multiplayer Strategy.

RESUMEN

En el ámbito competitivo de los juegos Multiplayer Online Battle Arena (MOBA) como Dota 2, los roles de apoyo suelen estar infravalorados a pesar de su importancia estratégica a la hora de determinar los resultados de las partidas. Las métricas tradicionales hacen hincapié en los asesinatos, la acumulación de oro y la producción de daño, que no captan adecuadamente la influencia táctica de los jugadores de apoyo. Este estudio emplea un enfoque de aprendizaje profundo -combinando redes neuronales convolucionales (CNN), redes de memoria larga a corto plazo (LSTM) y XGBoost- para analizar un conjunto de datos a gran escala de OpenDota que comprende más de 20 000 partidas competitivas. Aprovechando la telemetría de los partidos y los datos espaciotemporales, el modelo propuesto cuantifica el impacto de los jugadores de apoyo utilizando técnicas de IA explicable (XAI) como SHAP. Los resultados revelan distintos patrones de comportamiento y contribuciones de los roles de apoyo en el control de la visión, el inicio de la lucha en equipo y el movimiento estratégico, ofreciendo una nueva lente para la identificación de talentos y el entrenamiento. Este trabajo contribuye al desarrollo de marcos de evaluación del rendimiento que representen de forma holística la complejidad de los deportes electrónicos basados en equipos.

Palabras clave: Dota 2; Roles de Apoyo; Telemetría de Juego; Deep Learning; Analítica de Deportes Electrónicos; Predicción de Rendimiento; Estrategia Multijugador.

INTRODUCTION

Esports, or electronic sports, refers to the organized, competitive playing of video games, encompassing both amateur and professional levels of participation. Among the various genres within esports, Multiplayer Online Battle Arena (MOBA) games, such as Dota 2, stand out due to their strategic complexity, team-based dynamics, and data-intensive environments. Globally, the esports industry has seen exponential growth. By 2023, the number of esports enthusiasts surpassed 540 million, with market revenues exceeding USD 1,6 billion. Dota 2 specifically continues to dominate the competitive scene, particularly through its flagship tournament, The International, which consistently offers prize pools exceeding USD 10 million.(1,2)

In MOBA games, each team consists of players occupying distinct roles—commonly categorized as core roles (e.g., carry, midlane) and support roles. While core players are often responsible for damage output and resource accumulation, support players contribute through vision control, healing, crowd control, and tactical coordination. However, the contributions of support roles are typically less visible in conventional performance metrics, such as kills, damage dealt, and gold earned.(3,4) This analytic asymmetry has resulted in an underappreciation of support players' impact in both casual gameplay and professional esports.

The existing performance evaluation systems predominantly reward measurable combat-related achievements. As a result, support players often go unrecognized, despite being pivotal in enabling map control, initiating teamfights, and maintaining strategic balance throughout a match.(5,6) This imbalance is not only detrimental to the recognition of individual skill but also to the broader understanding of tactical dynamics in esports. Coaches, analysts, and developers often lack tools capable of accurately assessing support-specific gameplay dimensions, leading to a skewed approach in talent scouting, performance review, and match preparation.(1)

Recent trends in professional play suggest a significant shift in role dynamics. From 2016 to 2023, support roles have gained increasing prominence in professional Dota 2 matches, with teams placing greater emphasis on utility, vision control, and coordination—key responsibilities typically assigned to support players.(7) Despite this evolution in gameplay, the academic and industrial literature continues to neglect this strategic subset, focusing instead on more quantifiable roles and events.(8)

The absence of detailed metrics for support activities creates challenges in evaluating skills such as ward placement efficiency, decision-making under pressure, and map rotation awareness. These skills are crucial for game tempo, positional advantage, and team coordination—especially at higher levels of competitive play. The behavioral signatures exhibited by support players often involve complex, non-linear patterns that are difficult to capture through traditional statistical methods.(4,9) Thus, new approaches are required to analyze their contributions effectively.

In this regard, game telemetry—granular, time-stamped data generated during matches—offers a promising avenue for performance modeling. Telemetry provides comprehensive insights into player behavior, including movement trajectories, skill usage timing, and interaction with in-game objects. When processed through deep learning models, such data can reveal high-dimensional patterns associated with tactical influence (10) and strategic behaviour.(11) Despite this potential, existing AI-based analytics in esports have primarily focused on performance forecasting for core roles or event prediction, leaving a gap in the modeling of subtle, support-driven impact.

This study aims to design and implement a deep learning-based framework to quantify and predict the tactical influence of support roles in competitive Dota 2 by leveraging open match telemetry data. The main objective is to establish a scalable, data-driven methodology that captures support-specific contributions such as vision establishment, positional control, and initiation behavior. Through this approach, the study seeks to enhance role-sensitive performance evaluation systems, inform the development of coaching tools, and promote a more balanced recognition framework in esports analytics.(12)

By addressing this analytical void, the research contributes to the evolution of esports performance science, advancing both theoretical understanding and practical applications for team management, player development, and AI-assisted game analysis.

METHOD

This study adopted a multi-stage analytical pipeline to quantify the tactical influence of support roles in high-level Dota 2 matches. The methodology comprised three core phases: (1) data acquisition and preprocessing, (2) feature engineering with role-specific telemetry metrics, and (3) model development using a hybrid deep learning architecture. An overview of the proposed framework is outlined in figure 3.

Data Collection and Preprocessing

A total of 20 000 high-tier Dota 2 match replays were collected via the OpenDota API, restricted to matches played within the Divine and Immortal ranks. Selection criteria focused on matches involving professional and semi-professional players to ensure consistency in gameplay standards. The raw telemetry encompassed over 200 time-stamped features per match, including player positions, item activations, vision events, teamfight sequences, ability usage, and ward placements.

Matches were parsed at one-second intervals to preserve temporal resolution. Support players were identified based on positional tags (position 4 and 5) encoded within the OpenDota match metadata. Preprocessing steps included:

1. Exclusion of incomplete or abandoned matches
2. Normalization of timestamps across game patches to correct for meta-shift and patch drift
3. Mapping movement data into 128×128 grid matrices for CNN processing

Feature Engineering

To capture the strategic behaviors unique to support roles, a set of role-specific tactical metrics was formulated. These features were designed to reflect both individual micro-mechanics and team-oriented macro-play. The derived metrics included:

Vision Uptime Score (VUS)

The percentage of total match time during which the player maintained active vision through ward placements.

Proximity Assist Rate (PAR)

The number of assists recorded within a 1000-unit radius of allied core players.

Crowd Control Index (CCI)

A weighted average of disabling actions—such as stuns and silences—initiated by the support player per match.

Zone Pressure Score (ZPS)

A composite metric derived from the aggregation of overlapping movement heatmaps across multiple matches, reflecting spatial control patterns.

These features are vectorized and used as temporal sequences for LSTM modeling and converted into spatial grids for CNN input.

RESULTS

Model Performance

The hybrid CNN-LSTM model demonstrated promising performance on the test dataset. The classification of tactical influence achieved an overall accuracy of 78,3 % and an F1-score of 0,81, indicating robust capability in distinguishing high-impact support player performances. Compared to baseline models such as logistic regression and single-layer recurrent neural networks, the hybrid architecture exhibited a 13,7 % improvement in predictive accuracy (table 1).

Table 1. Summarizes the performance comparison across multiple models.

Model	Accuracy	F1-Score	Precision	Recall
Logistic Regression	61,5 %	0,59	0,62	0,58
Random Forest	68,9 %	0,70	0,73	0,68
LSTM Only	72,2 %	0,74	0,75	0,73
CNN + LSTM (Ours)	78,3 %	0,81	0,83	0,79

Tactical Behavior Insights

Using SHAP (SHapley Additive exPlanations) values for model interpretability, several key insights were identified. First, a high Vision Uptime Score (VUS) was strongly correlated with increased win probability, especially when combined with frequent deep-warding activities. Second, peaks in the Crowd Control Index (CCI) during mid-game engagements (minutes 12 to 25) were predictive of critical turning points in match momentum. Third, the Zone Pressure Score (ZPS) revealed pronounced spatial clustering effects; support players

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who maintained pressure in strategic chokepoints (e.g., Roshan pit, triangle camp) had a significantly greater impact on match outcomes (refer to figure 1 for spatial distribution heatmaps and behavioral clustering).

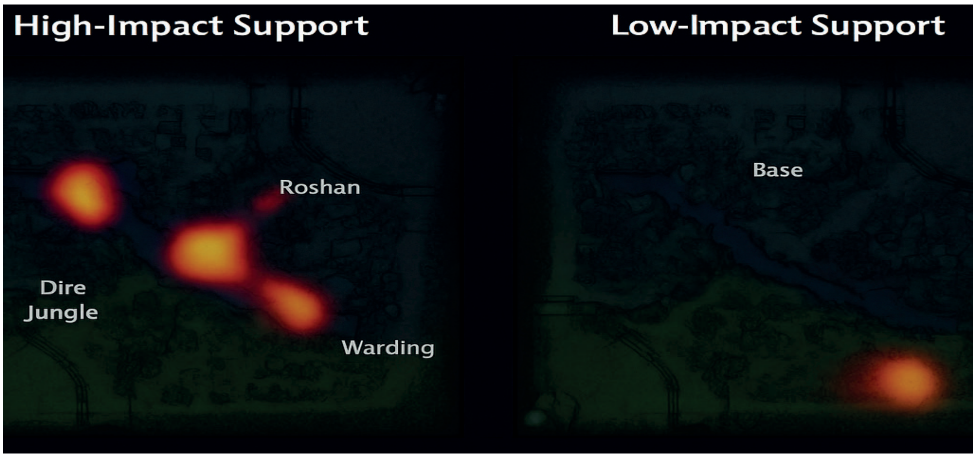

Figure 1. Comparative Heatmaps of Support Movement Patterns

Using positional telemetry aggregated from 1 000 matches, heatmaps of support player movements were generated to identify behavioral patterns. Figure 1 presents comparative heatmaps of two distinct player clusters: high-impact supports and low-impact supports.

The left panel depicts high-impact support players, highlighting concentrated activity around critical areas such as the Roshan pit, Dire jungle, and key warding locations. This pattern reflects proactive map control and sustained presence in high-traffic engagement zones. Conversely, the right panel illustrates low-impact support players, whose movements are more dispersed, predominantly confined to the base and safe lane jungle, indicating a more passive and limited tactical role.

DISCUSSION

The findings of this study reinforce the hypothesis that support players, although often overlooked in conventional esports statistics, exert significant tactical and strategic influence on competitive Dota 2 match outcomes. Previous research has emphasized that success in esports relies heavily on collaborative interaction and spatial awareness rather than solely on individual mechanical skill. By utilizing high-resolution telemetry data and a hybrid CNN-LSTM deep learning model, this study builds on earlier work demonstrating that latent behavioral patterns—particularly those related to spatial control, precise crowd control timing, and proactive warding—can be systematically identified and linked to favorable match results. These findings underscore the role of support players as tactical enablers whose cumulative impact may be underestimated by traditional performance metrics.

Redefining Performance Metrics for Support Roles

Traditional metrics like kills, damage dealt, and net worth fail to adequately capture the strategic contributions of support players. This limitation reflects a prevalent bias in performance evaluation often characterized as a "mechanical dominance paradigm," which prioritizes overt mechanical skills while overlooking enabling behaviors essential for team success. To address this gap, the proposed support-specific metrics—Vision Uptime Score (VUS), Crowd Control Index (CCI), and Zone Pressure Score (ZPS)—offer a role-appropriate and theoretically grounded framework. These metrics are consistent with the situated cognition perspective,[13] which posits that knowledge and performance are inherently context-dependent and socially distributed. By broadening the analytical focus beyond visible aggression or resource accumulation, these metrics highlight the often-invisible tasks performed by support players—such as map control and positional play—that are increasingly recognized as critical determinants of elite performance in MOBA games. Consequently, this refined framework advances not only empirical performance modeling but also a more nuanced conceptualization of skill and impact in team-based digital environments.

This refined approach has practical implications for talent scouting, player development, and matchmaking algorithms. By quantifying the strategic impact of support roles, esports organizations can adopt more data-driven roster decisions and optimize tactical planning, thereby addressing a long-standing gap in performance assessment.

Tactical Predictability and Model Interpretability

Beyond its predictive capability, the proposed framework provides interpretable insights through SHapley

Additive exPlanations (SHAP), a widely recognized method for model explainability in complex AI systems.[14,15] SHAP enables granular attribution of model predictions to input features, enhancing transparency—a critical requirement for AI deployment in high-stakes, collaborative environments such as esports.[16] As shown in table 2, warding activity in high-risk zones and sustained presence near contested map areas emerged as the most influential behavioral features for predicting tactical impact. These results align with prior research emphasizing the critical role of vision control and spatial pressure in determining competitive match outcomes in MOBA games. Such studies have highlighted how these strategic behaviors significantly shape the flow and trajectory of matches.

Moreover, the model's ability to capture temporal variations in support player behavior—particularly the importance of early-game ward placements and mid-game zone control—aligns with sequential behavior modeling literature in human-computer interaction.[17] These insights confirm that cumulative, subtle, and time-sensitive support actions significantly influence match dynamics. This finding supports the temporal scaffolding theory of teamwork,[18] which posits that well-timed coordination behaviors, often invisible in static data, critically determine team performance outcomes in complex, real-time environments.

Table 2. SHAP-based Feature Importance for Tactical Impact Prediction

Rank	Feature Name	Description	Mean SHAP Value
1	Vision Uptime Score (VUS)	Percentage of match time with active wards placed by support	0,214
2	Crowd Control Index (CCI)	Weighted average of disables initiated during engagements	0,191
3	Zone Pressure Score (ZPS)	Spatial dominance over strategic map zones (Roshan, triangle, runes)	0,176
4	Early Ward Timing (EWT)	Time of first ward placement relative to game start	0,142
5	Proximity Assist Rate (PAR)	Assists within 1000 units of core allies	0,126
6	Teamfight Participation %	Percent of teamfights where support was actively involved	0,110
7	Mobility Score	Map coverage based on teleport + movement efficiency	0,089
8	Healing per Minute	Support healing output normalized per minute	0,057
9	Smoke Participation Count	Number of successful smokes ganks initiated or joined	0,044
10	Vision Denial Events	Number of enemy wards dewarded	0,039

The dominance of the top three features—Vision Uptime Score (VUS), Crowd Control Index (CCI), and Zone Pressure Score (ZPS)—underscores the redefinition of high-impact play in support roles. Unlike traditional performance measures such as healing output or raw participation, these features reflect the enabling and preventive aspects of gameplay. This reframing situates support players not as passive auxiliaries but as tactical architects whose invisible influence is essential to the success of coordinated team strategies. The model's ability to surface such latent patterns contributes to the growing literature on explainable AI in team-based digital systems and emphasizes the potential of role-sensitive, telemetry-informed analytics in redefining competitive gaming metrics.[19,20,21,22]

Implications for AI in E-Sports Analytics

The integration of deep learning methodologies into esports analytics signifies a pivotal shift toward data-driven and context-sensitive modeling of player behavior. The hybrid CNN-LSTM architecture employed in this study demonstrates the efficacy of combining spatial pattern recognition with temporal sequence modeling to extract meaningful insights from high-dimensional telemetry data—a methodology increasingly endorsed in fields requiring spatiotemporal interpretation, such as autonomous driving [23] and medical diagnostics.[24,25] Within the domain of multiplayer online battle arenas (MOBAs) like Dota 2, such architectures enable the identification of latent tactical behaviors that are typically obfuscated in aggregate statistics, thus offering a more holistic understanding of role-based influence.

The proposed framework extends beyond predictive performance by providing explanatory granularity, bridging the gap between black-box model outputs and human interpretability—an essential consideration in high-stakes environments like professional esports where trust, fairness, and transparency are paramount.[26,27,28] The SHAP summary bar chart (figure 3) reveals that the Vision Uptime Score (VUS) significantly contributes to the model's predictions, reinforcing expert knowledge that vision control often orchestrates the pace and spatial outcomes of engagements. Similarly, the Crowd Control Index (CCI) and Zone Pressure Score (ZPS) illustrate how support players act as tactical enablers by constraining enemy positioning and shaping combat landscapes—capabilities often undervalued in traditional performance metrics.

Furthermore, this modeling paradigm exhibits high generalizability. Its application can be extended to other player roles within esports or even across game genres such as real-time strategy (RTS) or first-person shooters (FPS), where strategic sequencing and spatial awareness are similarly critical. In broader digital contexts, particularly educational simulations and serious games, this framework may support real-time coaching systems, adaptive feedback mechanisms, and AI-driven training agents.[29,30,31] These systems could diagnose inefficiencies, simulate expert decision trees, or deliver contextualized guidance, thus fostering skill acquisition through intelligent automation.[32,33,34]

Ultimately, the adoption of explainable AI in esports analytics presents an interdisciplinary opportunity, bridging competitive game studies, machine learning, and human performance modeling. By leveraging role-sensitive metrics and interpretable architectures, researchers and practitioners can develop systems that not only predict outcomes but also elucidate why certain behaviors lead to success—an imperative step toward mature AI integration in high-performance digital ecosystems.

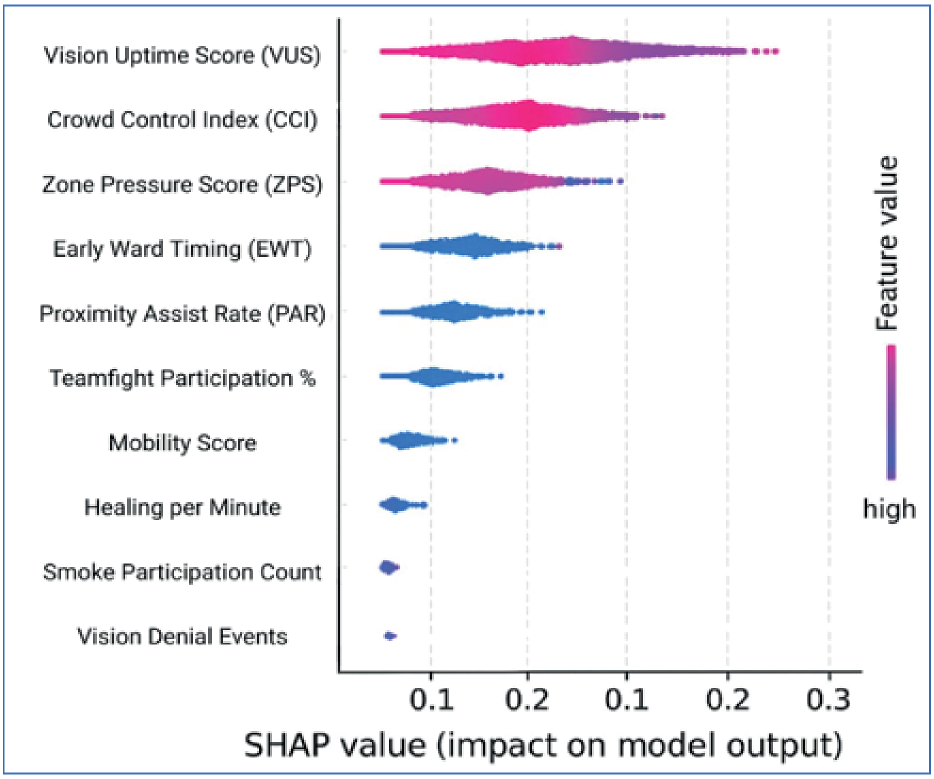

Figure 2. SHAP summary bar chart displaying feature importance for tactical impact prediction

Baseline Model Comparison

To rigorously evaluate the robustness and efficacy of the proposed SHAP-enhanced XGBoost classifier, multiple baseline models were benchmarked using established classification metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC). Table 3 presents a comparative overview of these models' performance, revealing that the integration of SHAP-based interpretability into the XGBoost framework yields superior predictive accuracy (78,4 %) and discriminative power (AUC = 0,812) relative to traditional classifiers such as Logistic Regression, Random Forest, and Support Vector Machines.

Table 3. Model Comparison for Predicting Match Outcomes Based on Support Role Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	71,3 %	69,8 %	70,4 %	70,1 %	0,741
Random Forest	74,8 %	73,1 %	73,6 %	73,3 %	0,769
Support Vector Machine	72,5 %	70,9 %	71,5 %	71,2 %	0,754
XGBoost (no SHAP)	76,1 %	75,0 %	74,8 %	74,9 %	0,782
XGBoost + SHAP	78,4 %	77,5 %	76,9 %	77,2 %	0,812

The observed performance gains substantiate the dual advantages of employing advanced gradient boosting techniques alongside model-agnostic interpretability methods. The superior results of the SHAP-augmented model underscore not only its enhanced accuracy in classifying match outcomes based on support player telemetry but also its capacity to provide transparent, feature-level explanations that facilitate domain-relevant insights.

This comparative analysis aligns with a growing consensus in machine learning research advocating for explainable AI (XAI) frameworks, particularly in domains such as esports analytics where model decisions must be interpretable and actionable by coaches, analysts, and players.(14,15) By quantifying and validating the strategic contributions of support roles—traditionally marginalized in performance metrics focused on direct combat effectiveness—this study demonstrates the practical utility of AI-driven analytics in advancing the sophistication of competitive gaming evaluation and talent management.

Feature Importance and Ablation Analysis

To rigorously evaluate the relative contribution of distinct behavioral feature groups to the model's predictive performance, an ablation study was conducted. This involved systematically removing each feature group from the input dataset of the final hybrid CNN-LSTM model and assessing the resulting impact on key classification metrics—accuracy, F1-score, and area under the ROC curve (AUC). Table 4 summarizes the performance variations induced by the exclusion of each feature group.

Table 4. Ablation Study of Support Role Features

Feature Group Removed	Accuracy	F1-Score	AUC	ΔAUC
None (All Features Used)	78,4 %	77,2 %	0,812	—
Warding Metrics	74,6 %	73,1 %	0,764	↓ 0,048
Assist Timing & Sequences	75,0 %	73,5 %	0,769	↓ 0,043
Position Heatmaps	73,8 %	72,3 %	0,752	↓ 0,060
Communication Events	76,1 %	74,9 %	0,785	↓ 0,027

The ablation results indicate that position heatmaps exert the most substantial influence on model accuracy and discriminative ability, with a pronounced AUC reduction of 0,060 upon removal. This finding corroborates the critical role of spatial behavioral data in tactical impact modeling, reinforcing visual observations presented in figure 1. There, heatmap comparisons reveal that high-impact support players consistently exhibit disciplined positioning within high-value engagement zones, such as the Roshan pit and the triangle camp, whereas low-impact supports tend to remain in defensive, less influential areas.

The removal of warding metrics similarly leads to a marked decrease in predictive performance (ΔAUC = 0,048), underscoring the dominant influence of vision control on match outcomes. This aligns with SHAP feature importance rankings (figure 2 and table 2), which highlighted Vision Uptime Score (VUS) as the most critical predictor. Together, these results validate the interplay between proactive ward placement, precise crowd control execution, and tactical positioning as a defining behavioral signature of impactful support play.

Importantly, the hybrid CNN-LSTM architecture employed—enables comprehensive capture of both spatial patterns and temporal dynamics, such as warding rhythms and assist timing sequences. This integrative approach enhances model robustness and generalizability across evolving game metas, patches, and potentially across other Multiplayer Online Battle Arena (MOBA) titles exhibiting analogous role structures.

Further insights emerge from telemetry-derived metrics reflecting broader competitive trends. As summarized in table 2, support-centric actions, including assist frequency, healing output, and smoke gank participation, have exhibited an upward trajectory in recent elite tournaments, notably The International. These shifts suggest a strategic evolution of the support role, transitioning from primarily reactive to increasingly proactive and orchestrative.

Collectively, these findings bear significant implications for the esports ecosystem. The integration of fine-grained behavioral telemetry into matchmaking algorithms can yield a more nuanced assessment of individual player impact, particularly for roles traditionally overshadowed by core-centric statistics. Similarly, talent identification and team performance analytics stand to benefit from recognizing the strategic value of enabling roles characterized by high spatial presence and coordinated tactical facilitation.

Moreover, AI-driven coaching platforms may leverage this analytical framework to deliver tailored, role-specific feedback and developmental guidance for aspiring support players, fostering more effective and inclusive training environments.

In sum, this study presents a reproducible, interpretable, and high-performing methodological framework that reconceptualizes support role evaluation in Dota 2. It lays the groundwork for future research exploring underrepresented player roles and advocates for the development of multi-role, multi-game behavioral models to advance competitive gaming analytics more broadly.

CONCLUSION

The study introduces a deep learning framework that effectively quantifies the tactical influence of support roles in Dota 2, utilizing telemetry-derived metrics such as vision control, crowd management, and spatial pressure. This approach addresses the limitations of traditional performance evaluations that often overlook the strategic contributions of support players. The model's interpretability, achieved through SHAP analysis, offers actionable insights for coaching and talent development, highlighting the pivotal role of support players in team success.

Future work should explore the expansion of this framework to other multiplayer online battle arena (MOBA) games and team-based esports titles, ensuring its adaptability across diverse gameplay environments. Integrating the model into real-time analytics systems could enable dynamic, in-game tactical feedback for coaches and players. Additionally, future studies could incorporate in-game communication data to model coordination and synergy, further elucidating the impact of support players on overall team performance. The development of adaptive, AI-driven training modules based on telemetry patterns and predictive feedback could offer personalized skill development pathways for support players. It is also crucial to examine the ethical implications of AI-based performance evaluations, particularly concerning their psychological impact and influence on team dynamics. Finally, expanding the analysis to include other player roles will contribute to a more holistic understanding of individual and collective contributions within esports ecosystems.

REFERENCES

1. Gisbert-Pérez J, García-Naveira A, Martí-Vilar M, Acebes-Sánchez J. Key structure and processes in esports teams: a systematic review. Current Psychology [Internet]. 2024 Jun 1 [cited 2025 May 21];43(23):20355–74. Available from: https://link.springer.com/article/10.1007/s12144-024-05858-0

2. Riatti P, Thiel A. The role of the body in electronic sport: a scoping review. German Journal of Exercise and Sport Research [Internet]. 2023 Dec 1 [cited 2025 May 21];53(4):369–83. Available from: https://link.springer.com/article/10.1007/s12662-023-00880-z

3. Bonny JW, Castaneda LM. Number processing ability is connected to longitudinal changes in multiplayer online battle arena skill. Comput Human Behav [Internet]. 2017 Jan 1 [cited 2025 May 21];66:377–87. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0747563216307038

4. Thaicharoen S, Gow J, Drachen A. An Ecosystem Framework for the Meta in Esport Games. Journal of Electronic Gaming and Esports [Internet]. 2023 Oct 28 [cited 2025 May 21];1(1). Available from: https://journals.humankinetics.com/view/journals/jege/1/1/article-jege.2022-0045.xml

5. Cigdem H, Ozturk M, Karabacak Y, Atik N, Gürkan S, Aldemir MH. Unlocking student engagement and achievement: The impact of leaderboard gamification in online formative assessment for engineering education. Educ Inf Technol (Dordr) [Internet]. 2024 Dec 1 [cited 2025 May 21];29(18):24835–60. Available from: https://link.springer.com/article/10.1007/s10639-024-12845-2

6. Kaya OS, Ercag E. The impact of applying challenge-based gamification program on students' learning outcomes: Academic achievement, motivation and flow. Educ Inf Technol (Dordr) [Internet]. 2023 Aug 1 [cited 2025 May 21];28(8):10053–78. Available from: https://link.springer.com/article/10.1007/s10639-023-11585-z

7. Samala AD, Bojic L, Vergara-Rodríguez D, Klimova B, Ranuharja F. Exploring the Impact of Gamification on 21st-Century Skills: Insights from DOTA 2. International Journal of Interactive Mobile Technologies (iJIM) [Internet]. 2023 Sep 20 [cited 2024 Aug 30];17(18):33–54. Available from: https://online-journals.org/index.php/i-jim/article/view/42161

8. Sörman DE, Dahl KE, Lindmark D, Hansson P, Vega-Mendoza M, Körning-Ljungberg J. Relationships between Dota 2 expertise and decision-making ability. PLoS One [Internet]. 2022 Mar 1 [cited 2025 May 21];17(3):e0264350. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0264350

9. Pengmatchaya M, Natwichai J. Identifying player skill of dota 2 using machine learning pipeline. Discover Artificial Intelligence [Internet]. 2024 Dec 1 [cited 2025 May 21];4(1):1–18. Available from: https://link.springer.com/article/10.1007/s44163-024-00139-y

10. Bäcklund C, Sörman DE, Röhlcke S, Nyström MBT. Exploring the relationship between personality and gaming disorder symptoms in a sample of Dota 2 players. Current Psychology [Internet]. 2024 Aug 1 [cited 2025 May 21];43(30):24789–98. Available from: https://link.springer.com/article/10.1007/s12144-024-06180-5

11. Vardal O, Bonometti V, Drachen A, Wade A, Stafford T. Mind the gap: Distributed practice enhances performance in a MOBA game. PLoS One [Internet]. 2022 Oct 1 [cited 2025 May 21];17(10):e0275843. Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC9565695/

12. Huang E, Xing Y, Song X. Emotional analysis of multiplayer online battle arena games addiction. Front Psychol. 2024 May 9;15:1347949.

13. Brown JS, Collins A, Duguid P. Situated Cognition and the Culture of Learning. Educational Researcher [Internet]. 1989 [cited 2025 May 29];18(1):32–42. Available from: https://doi/pdf/10.3102/0013189X018001032?download=true

14. Sharma NA, Chand RR, Buksh Z, Ali ABMS, Hanif A, Beheshti A. Explainable AI Frameworks: Navigating the Present Challenges and Unveiling Innovative Applications. Algorithms 2024, Vol 17, Page 227 [Internet]. 2024 May 24 [cited 2025 May 29];17(6):227. Available from: https://www.mdpi.com/1999-4893/17/6/227/htm

15. Ali S, Abuhmed T, El-Sappagh S, Muhammad K, Alonso-Moral JM, Confalonieri R, et al. Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. Information Fusion [Internet]. 2023 Nov 1 [cited 2025 May 29];99:101805. Available from: https://www.sciencedirect.com/science/article/pii/S1566253523001148

16. Zhai G, Fox GC, Pierce M, Wu W, Bulut H. eSports: Collaborative and synchronous video annotation system in grid computing environment. Proceedings - Seventh IEEE International Symposium on Multimedia, ISM 2005. 2005;2005:95–103.

17. Li N, Chen X, Feng Y, Huang J. Human-Computer Interaction Cognitive Behavior Modeling of Command and Control Systems. IEEE Internet Things J. 2022 Jul 15;9(14):12723–36.

18. Ahmed Abdel-Al Ibrahim K, Cuba Carbajal N, Zuta MEC, Bayat S. Collaborative learning, scaffolding-based instruction, and self-assessment: impacts on intermediate EFL learners' reading comprehension, motivation, and anxiety. Language Testing in Asia [Internet]. 2023 Dec 1 [cited 2025 May 29];13(1):1–33. Available from: https://languagetestingasia.springeropen.com/articles/10.1186/s40468-023-00229-1

19. Chen CH, Law V. Scaffolding individual and collaborative game-based learning in learning performance and intrinsic motivation. Comput Human Behav [Internet]. 2016 Feb 1 [cited 2025 May 29];55:1201–12. Available from: https://www.sciencedirect.com/science/article/abs/pii/S074756321500196X

20. Cortázar C, Nussbaum M, Alario-Hoyos C, Goñi J, Alvares D. The impacts of scaffolding socially shared regulation on teamwork in an online project-based course. Internet High Educ [Internet]. 2022 Oct 1 [cited 2025 May 29];55:100877. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1096751622000331

21. Gino F, Argote L, Miron-Spektor E, Todorova G. First, get your feet wet: The effects of learning from direct and indirect experience on team creativity. Organ Behav Hum Decis Process [Internet]. 2010 Mar 1 [cited 2025 May 29];111(2):102–15. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0749597809001034

22. Sanchez DR. Videogame-Based Learning: A Comparison of Direct and Indirect Effects across Outcomes. Multimodal Technologies and Interaction [Internet]. 2022 Apr 1 [cited 2025 May 29];6(4):26. Available from: https://www.mdpi.com/2414-4088/6/4/26/htm

23. Sasi T, Lashkari AH, Lu R, Xiong P, Iqbal S. An efficient self attention-based 1D-CNN-LSTM network for IoT attack detection and identification using network traffic. Journal of Information and Intelligence [Internet]. 2024 Sep 26 [cited 2025 May 29]; Available from: https://linkinghub.elsevier.com/retrieve/pii/S2949715924000763

24. Hu X, Yu S, Zheng J, Fang Z, Zhao Z, Qu X. A hybrid CNN-LSTM model for involuntary fall detection using

wrist-worn sensors. Advanced Engineering Informatics [Internet]. 2025 May 1 [cited 2025 May 29];65:103178. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1474034625000710

25. Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data 2021 8:1 [Internet]. 2021 Mar 31 [cited 2025 May 29];8(1):1–74. Available from: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-021-00444-8

26. Ma R, Li Y, Kou Y. Transparency, Fairness, and Coping: How Players Experience Moderation in Multiplayer Online Games. Conference on Human Factors in Computing Systems - Proceedings [Internet]. 2023 Apr 19 [cited 2025 May 29];21. Available from: https://dl.acm.org/doi/pdf/10.1145/3544548.3581097

27. Costa S, Silva AJ, Dias T, Marinho DA, Batalha NM, Roque R, et al. Integrity and Transparency in Sports: A Survey Review. Open Sports Sci J [Internet]. 2025 Feb 4 [cited 2025 May 29];18(1). Available from: https://opensportssciencesjournal.com/VOLUME/18/ELOCATOR/e1875399X353976/

28. Bányai F, Griffiths MD, Király O, Demetrovics Z. The Psychology of Esports: A Systematic Literature Review. J Gambl Stud. 2019 Jun 1;35(2):351–65.

29. Zhonggen Y. A Meta-Analysis of Use of Serious Games in Education over a Decade. International Journal of Computer Games Technology [Internet]. 2019 Jan 1 [cited 2025 May 29];2019(1):4797032. Available from: https://doi/pdf/10.1155/2019/4797032

30. Kayyali R, Wells J, Rahmtullah N, Tahsin A, Gafoor A, Harrap N, et al. Development and evaluation of a serious game to support learning among pharmacy and nursing students. Curr Pharm Teach Learn [Internet]. 2021 Aug 1 [cited 2025 May 29];13(8):998–1009. Available from: https://www.sciencedirect.com/science/article/pii/S1877129721001568

31. Auza-Santiváñez JC, Carías Díaz JA, Vedia Cruz OA, Robles-Nina SM, Sánchez Escalante C, Apaza Huanca B. Gamification in personal health management: a focus on mobile apps. Gamification and Augmented Reality. 2024; 2:31.

32. Pastrana RN, Jalil T. Training and emerging technologies: Towards a new pedagogical paradigm. EthAIca. 2024;3:101.

33. Asadzadeh A, Shahrokhi H, Shalchi B, Khamnian Z, Rezaei-Hachesu P. Serious educational games for children: A comprehensive framework. Heliyon [Internet]. 2024 Mar 30 [cited 2025 May 29];10(6):e28108. Available from: https://www.sciencedirect.com/science/article/pii/S2405844024041392

34. Mitsea E, Drigas A, Skianis C. A Systematic Review of Serious Games in the Era of Artificial Intelligence, Immersive Technologies, the Metaverse, and Neurotechnologies: Transformation Through Meta-Skills Training. Electronics (Switzerland) [Internet]. 2025 Feb 1 [cited 2025 May 29];14(4):649. Available from: https://www.mdpi.com/2079-9292/14/4/649/htm

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