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Review Article

Machine Learning Applications in Multiplayer Online Battle Arena Esports—A Systematic Review

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ABSTRACT

Machine learning (ML) is an emerging field, while multiplayer online battle arena (MOBA) esports has seen a rise as a research subject of interest. The applications of ML in MOBA are an interesting field of study as the esports genre is enriched by a plethora of data. Moreover, the MOBA esports industry is a budding economic sector with stakeholders looking for innovative scientific studies. This necessitates the need for a systematic review to provide insights for future studies. The databases (Scopus, Web of Science, PubMed, ScienceDirect and Google Scholar) were systematically searched to identify published peer-reviewed academic articles. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method was used for the analysis. Papers were included if they contained ML applications for MOBA, excluding game design or non-esports-related studies. There are 35 studies included in this systematic review, with most studies on Defence of the Ancients 2 (DotA 2) and League of Legends (LoL). ML algorithms are used to make predictions for different purposes using game mechanics and player profiles as datasets, with random forests, decision trees, logistic regression, neural networks, and more. The performance of ML models was deemed impressive, given their simplicity and the datasets used. Key findings highlight the potential future area of research in the empowerment of mobile phone-based MOBA, commercialisation opportunities using ML technology in authentic settings, and overcoming challenges in data access and regional differences.

Keywords: Esports, machine learning, MOBA, PRISMA, systematic review

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INTRODUCTION

ML, a subfield of artificial intelligence (AI), is the field that focuses on the development of algorithms and models that can learn from and make predictions based on data, a so-called machine learning approach (Tan, 2022). ML involves the use of statistical and mathematical methods to enable computers to learn from data without being explicitly programmed to perform a specific task. ML is applied in a vast range of disciplines, from natural language processing and computer vision to finance and healthcare (Oyebode et al., 2023), leading to significant advances in our understanding and ability to solve authentic and complex problems (Sclavounos & Ma, 2018). ML helps researchers automate rigorous repetitive tasks, discover hidden patterns in data, and make predictions or decisions based on data (Truong et al., 2019; Zomlot et al., 2013). The impact of ML in research is constantly growing (Jordan & Mitchell, 2015) as more data is generated and new techniques are developed, making it a key area of study for researchers in various fields.

In recent years, esports, also known as electronic sports, has been a rapidly growing industry involving competitive video gaming (Reitman et al., 2020). It refers to organised, competitive multiplayer video gaming events that are played either online or in person and that often involve professional players and large prize pools, transforming hobbies into a rewarding career that may shake the economic sector (Railsback & Caporusso, 2019). Esports popularity in recent years attracted large audiences, both online and offline, and inspired the creation of numerous professional teams and leagues. For Malaysia, the recent national budget year 2024 showcased the importance of the growth of esports by allocating as much as RM30 million (Bernama, 2023). With the increasing interest in esports, it has also become a subject of academic research and exploration (Wan Jr et al., 2021; Meng-Lewis et al., 2022), with the goal of better understanding its potential for society and economy.

Currently, ML is having a significant impact on esports-related research in several ways. For instance, ML algorithms are used for performance analysis. With this, ML contributes to the analysis of game data and player performance, helping teams and players improve their strategies and decision-making processes (Kulkarni, 2012). Next, ML can also be used to train players by simulating game scenarios and providing personalised feedback. This can help players identify their strengths and weaknesses and improve their gameplay (Eisen, 2017). Other than that, ML algorithms are utilised to develop and enhance game features, such as recommendation systems, which can provide a better gaming experience for players (Fanca et al., 2020). Among others, ML is widely used to predict the outcome of esports matches and events, providing valuable insights for fans, players, and teams (Bailey, 2020). Overall, ML is having a positive impact on the esports industry by providing new tools and insights for players, teams, and fans to help drive innovation and growth in the industry. This study is intrigued to review the plethora of implementations of ML approaches for the benefits of esports with systematic tools.

One of the remarkably interesting esports genres that capitalised on ML approaches is MOBA esports, a competitive video game competition that focuses on real-time strategy gameplay (Yang et al., 2016). In MOBA esports, two teams of 5 players compete against each other, with each player controlling a single character (known as a “hero” or “champion”, depending on the game) with unique abilities and strengths. The goal of MOBA is for each team to destroy the opponent’s base, which is typically located at the opposite end of the game map. To do this, players must work together to defeat the opponent’s heroes and control key objectives on the map, such as towers, creeps or minions, and neutral monsters. MOBA esports have become increasingly popular in recent years, with games like DotA 2, LoL, and Heroes of the Storm attracting large audiences and offering substantial prize pools (Bankov, 2019). MOBA tournaments are often organised by game developers, esports organisations, or independent organisers and can be watched live or online by fans around the world. Thus, as avid fans of esports, we intend to fill the important gaps in the academic literature for MOBA esports towards embracing the future of AI through many facets of ML by asking the following research questions (RQ):

RQ1. What are the ML algorithms used in various MOBA esports research?

RQ2. How does the implementation of ML benefit MOBA esports?

RQ3. How well do the ML algorithms perform in the included studies?

RQ4. What is the potential risk of biases in the included studies?

RQ5. What are the various MOBA game features used as predictors?

RQ6. Which player skill levels and regions are being prominently researched in these fields?

RQ7. To what extent do humans need to intervene in applying ML for MOBA esports studies?

MATERIALS AND METHODS

Eligibility Criteria

Studies had to be peer-reviewed, published between 2010 and 2022, and written in English. All studies chosen were related to the application of ML for various purposes in MOBA esports. This included predicting wins from many forms of game mechanics and features to the development of AI to play MOBA games. Interestingly, an investigation into predicting toxic behaviour is also included. Similarly, a report on the application of ML for tournament live streaming, which is the media to display the gameplay between contestants, was also reviewed. Studies were excluded if they focused solely on game designs and structures without the aspect of esports. Other than that, reports on video game genres in esports other than MOBA, such as first-person shooter (FPS), fighting games, real-time strategy (RTS), battle royale (BR), and sports, are excluded from this review.

Information Sources

Online databases such as Scopus, Web of Science, PubMed, and ScienceDirect were systematically searched for relevant literature. However, the search was performed unsystematically for Google Scholar, and the results yielded more than a thousand returns. All the searches were performed and recorded in early January 2023, up until the end of November 2023.

Search Strategy

The search strings used in Scopus, Web of Science, PubMed, and ScienceDirect were shown in Table 1. However, the search string used for Google Scholar was altered to obtain a much more niche result (Table 1).

Table 1
The search string used in online databases and Google Scholar

Search strings in online databases	("electronic sports" OR esports OR e-sports OR "competitive video game" OR "multiplayer online games" OR moba OR "multiplayer online battle arena") AND "machine learning"
Search string in Google Scholar	("electronic sports" OR esports OR "multiplayer online games" OR moba OR "multiplayer online battle arena") AND "machine learning" -trial -review -book -sports

Selection Process

The first author independently searched for literature that met the inclusion criteria. The results from the search were exported in BibTeX format, enabling the second, third and fourth authors to upload them into a collaborative, online electronic programme. Next, the duplicated records were removed. Then, all authors screened the titles independently to ensure the reports were eligible for the full-text retrieval process. After that, we performed a screening by reading the abstracts and keywords to determine the finalised list for inclusion. During this process, the excluded papers were due to the fact that the reported esports games do not belong to the MOBA genre.

Data Collection Process

The electronic search results were uploaded into Mendeley Library, a reference management program for duplicate removal. The entire screening process was completed in the Mendeley workspace. Finally, the data extraction process was conducted manually in a Microsoft Excel sheet.

Data Items

All four authors were involved in the selection of our study outcomes by ensuring ML approaches were implemented and games from the MOBA genre. Table 2 shows the items extracted from the included studies. However, for certain item(s) with missing or unclear information, all the authors agreed to report as unspecified. For ML-based studies, it is difficult to assume certain information, data, or steps are taken by the researchers involved in the reported experiment and investigation, as this assumption can alter the entire process and results of the studies. Hence, the authors believed this mutual consensus is a more reliable and valid way of performing this review.

Table 2
Items extracted from the included studies for RQ1 to RQ3

RQ	Items extracted
RQ1	• Game name(s) • Game mechanic(s) • ML algorithm(s) • ML algorithm class(es) • ML tool(s)/software
RQ2	• Findings (discussion) • Limitations, if specified • Future area, if specified
RQ3	• ML metrics • ML challenges

Study Risk of Bias Assessment

In this systematic review, the process of assessing the quality of ML-based studies and publications is challenging due to the diverse nature of research in the field (Le Glaz et al., 2021). To date, there is a lack of standardised guidelines for evaluation purposes (Marshall & Wallace, 2019). However, a tool called prediction model risk of bias assessment tool (PROBAST) can assess the risk of bias and the applicability of diagnostic and prognostic prediction models (Wolff et al., 2019). PROBAST assess the risk of biases in 4 domains: participants, predictors, outcome, and analysis (de Jong et al., 2021), governed by signalling questions (such as *"Are the participants representative of the target population?"* or *"Was the outcome measured appropriately?"*) to determine the level of risk of bias (low, moderate or high) for a study (Navarro et al., 2020). PROBAST is useful and practical in ML-related works (Collins et al., 2021; Jiu et al., 2024; Yang et al., 2023).

In the event of disagreements during the bias assessment, the reviewers discussed the conflicting assessments to understand the reason and rationale for each perspective. If consensus was not reached through discussion, the final decision was made based on the majority opinion through the re-assessment of the evidence process. This guarantees that all disagreements were transparently resolved to ensure consistency and minimised bias in the overall assessment.

Synthesis Methods

The study design of the included works in this systematic review was expected to be heterogeneous, where they could have different study designs and scopes. This resulted in the authors having difficulties synthesising the results of the studies and performing statistical meta-analysis, as different study designs can have different limitations and sources of bias. However, the authors agreed that meta-analysis will be done as much as possible for equivalent criteria from multiple studies based on the data extracted. This includes distinguishable data distribution, individual frequency of occurrence, and collective mean with its distributions. Additionally, subgroup analyses are conducted to provide a more comprehensive analysis of ML applications in MOBA and yield richer insights.

RESULTS AND DISCUSSIONS

Study Selection

In Figure 1, the PRISMA flow diagram shows that 501 articles were identified in Scopus, Web of Science, PubMed ScienceDirect databases, and Google Scholar. After removing the duplicated articles (*n* = 29), the acquired articles underwent screening (*n* = 472). The titles and abstracts were screened, and some did not fit the inclusion criteria (*n* = 345). Therefore, the remaining studies were sought for retrieval (*n* = 127), but about half of them were not accessible (*n* = 51). Hence, the retrieved full-text articles were assessed for eligibility (*n* = 76). However, some studies have not been performed on games from the MOBA genre (*n* = 25) and have focused on non-game-related features and mechanics (*n* = 16). Finally, the eligible studies were included in this systematic review for the analysis (*n* = 35).

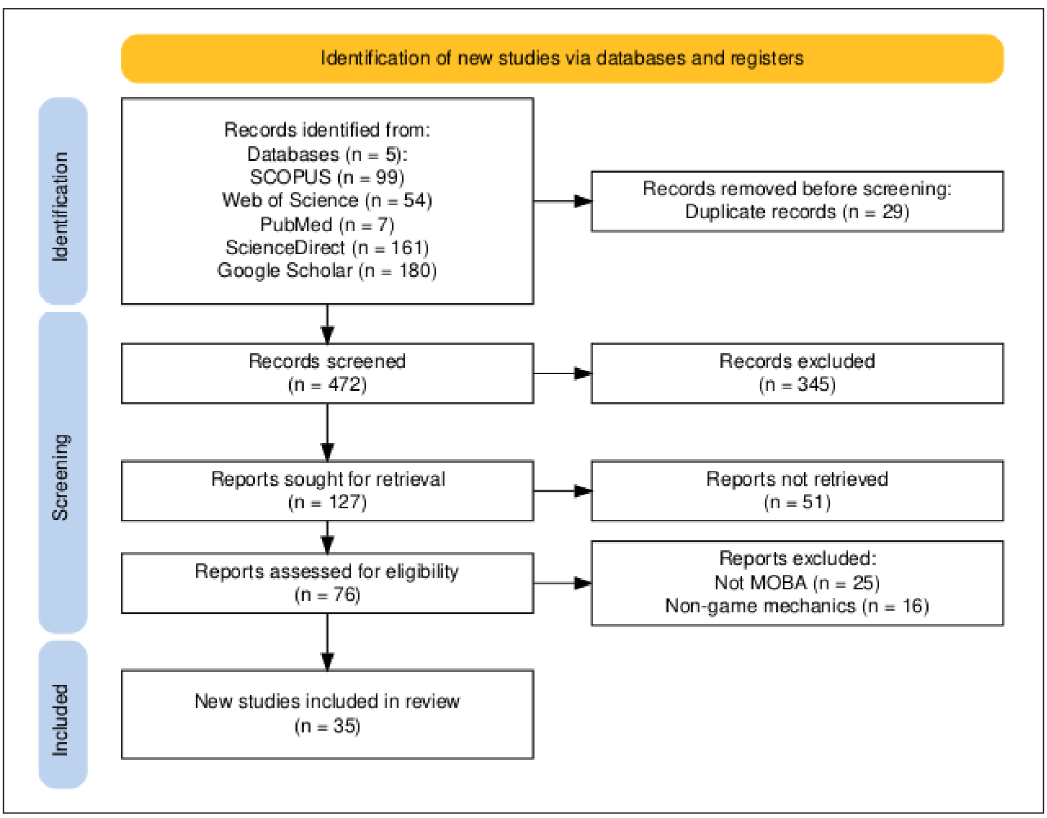

Figure 1. PRISMA flow diagram

Study Characteristics

Table 3 displays the study characteristics deployed by the authors of the 35 included studies. The description provided here is to answer RQ1. From the table, the most used games for ML-based studies are DotA 2, with 47.2%, followed by LoL, with 41.7% of the studies. Next is Honor of Kings (HoK) at 8.3% and For Honor at 2.8%. Figure 2 visually represents the game distributions for the 35 included studies.

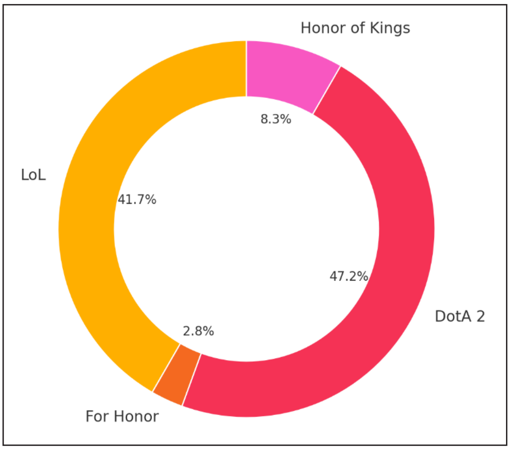

Figure 2. Game distributions from the included studies

Game mechanics include game and player datasets. Game datasets include data extracted before, during, and after the match. Pre-match data considers the state before the match, such as the hero or champion draft. In-match data is obtained during the match, like the first 10 minutes of match data. Some features include scores obtained by the players, such as gold earned, experience per minute (XPM), KDA ratio, vision point, and more. Post-match data is obtained after the match has ended, and statistics from the match include total camps stacked, gold per minute (GPM), total healing done, KDA of all players, and more. Player datasets were extracted from the players' profiles of the game, including winning rate, proficiency, and experience using certain heroes or champions, and match-making rating (MMR) was collected from their gameplay rating in the ranked game mode.

The ML algorithms deployed in the included studies are logistic regression (LR), support vector machines (SVM), k-nearest neighbours (k-NN), random forest (RF), Naïve Bayes (NB), decision tree (DT), support vector classification (SVC), gradient boosting (GBOOST), neural network (NN) (including deep NN), eXtreme Gradient Boosting Regressor (XGB), MultiLayer Perceptron (MLP), long short-term memory (LSTM) (one is modified as CBOW-LSTM), graph convolutional network (GCN), genetic algorithm, factorisation machines, XGBoost, and ExtraTree. Figure 3 shows the frequency of each algorithm reported in the included studies. The ML algorithms used in the studies include supervised, unsupervised, semi-supervised, reinforcement learning, and mixed. Most studies deployed supervised learning (73%), as can be seen in Figure 4.

The ML algorithm with the greatest number of applications for MOBA is RF. The earliest work related to ML is a DotA 2 hero selection recommendation system before the game using the LR model by Conley and Perry (2013), which amassed a high number of citations (42). A few more works with a similar approach include Kinkade and Lim (2015) and Song et al. (2015), which provide a better foundation for academic work on LR and DotA 2, specifically ML and MOBA.

Table 3
Study characteristics

Authors (year)	Game name(s)	Game mechanic(s)	ML algorithm(s)	ML algorithm class(es)	ML tool(s)/ software
Bahrololloomi et al. (2023)	LoL	Player experience-points per minute (XPM)	XGBoost, CatBoost, RF	Supervised Learning	Python, Featurewiz
Bisberg & Ferrara (2022)	LoL	30 features about matches and players: Match history, player performance metrics, gold earned, experience gained, kills, vision control	GCN-cheby	Semi-supervised learning	Python, TensorFlow
Canossa et al. (2021)	For Honor	36 features related to player behaviour, including activity modes, match performance, and chat actions	RF, SVM	Supervised Learning	Python (custom implementation)
Costa et al. (2021)	LoL	51 features include banned and picked champions, player statistics (win rate, games played, KDA)	RF, LR, SVM	Supervised Learning	R, Python
Da Silva et al. (2017)	LoL	Keystroke and mouse dynamics, including movement speed, click frequency, latency, and key combinations	MLP, BN, RBF Network	Supervised Learning	WEKA
Do et al. (2020)	LoL	Champion Mastery Points (CMP), normalised play frequency, top 5 champion preferences	SVD	Not specified	Python, Surprise library
Do et al. (2021)	LoL	Champion mastery points, player-champion win rate, total games played, recent games played	DNN, SVC, RF, GBoost, kNN	Supervised Learning	Python, Keras, Scikit-learn
Edge (2013)	DotA 2	Player churn behaviour, KDA ratio, player empowerment, progress towards goals	k-NN, NB, DT	Supervised Learning	WEKA
Franco et al. (2019)	DotA 2	36 player performance attributes, including Kills, Deaths, Assists, Gold per Minute, Hero Healing, and Observer Wards Placed	k-means clustering, Genetic Algorithm	Unsupervised Learning	Python, OpenDota API
Guzmán & Medina (2021)	LoL, Dota 2	165 variables including gold, creeps, assists, deaths, KDA ratio, items, roles	RF, LR, NN	Supervised Learning, Unsupervised Learning	Python, R, WEKA
Hodge et al. (2021)	LoL	Player performance metrics, including metrics like KillsR−D and NetworthR−D	RF, LightGBM	Supervised Learning	Python, CfsSubsetEval
Hong & Lee (2022)	LoL	Detection of in-game events using screen analysis; events include kills, tower, and inhibitor destruction	ResNet	Supervised Learning	Python

Table 3 *(continue)*

Authors (year)	Game name(s)	Game mechanic(s)	ML algorithm(s)	ML algorithm class(es)	ML tool(s)/ software
Jiang et al. (2020)	LoL	Contextual data such as champion type, match duration, player roles, and game versions	Neural Individualized Context-Aware Embeddings	Not specified	Python, Tensor Toolbox
Kim et al. (2020)	LoL	In-game data such as champion composition, gold, experience difference, and number of kills	MLP	Supervised Learning	Python, PyTorch
Kokkinakis et al. (2020)	DotA 2	Player performance, in-game events, match statistics	Various algorithms for data visualisation and storytelling	Unsupervised Learning	Weavr Companion App, custom analytics engine
Liang (2021)	LoL	38 features, including gold difference, experience difference, wards placed, kills, assists	SVM, DT	Supervised Learning	Python, Kaggle dataset
Luo et al. (2019)	DotA 2	In-game events like using Black King Bar, Roshan fight, tower destruction	ResNet152, Teacher-Student Model, Zero-Shot, Network Pruning	Supervised Learning	Python, PyTorch
Lyu et al. (2022)	DotA 2	152 behavioural features, including gold per minute, hero kills, experience per minute, ward placement, item usage	GPR, RF	Supervised Learning	WEKA, R
Marchenko & Suschevskiy (2018)	DotA 2	Player transfers, regions, Elo ratings, participation in The International, player roles, fantasy points	Exponential Random Graph Model (ERGM), Association Rules Mining	Mixed Methods	R, ERGM, Apriori algorithm
Martens et al. (2015)	DotA 2	Chat logs, player communication patterns, in-game events such as kills and match outcomes	NLP, SVM	Supervised Learning	Python, Scikit-learn
Mohammed et al. (2022)	DotA 2	Hero picks and bans during the drafting phase, focusing on team synergy and counter-picking strategies	CBOW, LSTM	Supervised Learning	Python, Gensim
Mora-Cantallops & Sicilia (2018)	LoL	Player networks, match history, structural network indicators like degree, betweenness, modularity	Affinity Propagation Clustering	Unsupervised Learning	Python, NetworkX, Gephi
do Nascimento Junior et al. (2017)	LoL	Player performance statistics such as gold earned, number of monsters killed, and total damage dealt	k-means clustering	Unsupervised Learning	Python

Table 3 *(continue)*

Authors (year)	Game name(s)	Game mechanic(s)	ML algorithm(s)	ML algorithm class(es)	ML tool(s)/ software
Porokhnenko et al. (2019)	DotA 2	Hero picks, team compositions, match outcomes	Linear Regression, SVM, NN	Supervised Learning	Python, Scikit-learn, TensorFlow
Prakannoppakun & Sinthupinyo (2016)	DotA 2	Player roles, kills, deaths, assists, gold per minute, hero damage	NN, MLP	Supervised Learning	Dota 2 API, Custom Model
Semenov et al. (2017)	DotA 2	Hero drafts, team composition, player skill levels	NB, LR, GBoost, Factorization Machines	Supervised Learning	Python, FastFM, XGBoost
Shen (2022)	LoL	First 10 minutes data, including kills, wards placed, gold difference, experience difference	AdaBoost, GBoost, RF, ExtraTree, SVM, NB, kNN, LR, DT	Supervised Learning	Python
Stanlly et al. (2022)	DotA 2	Hero and item choices, in-game stats, player behaviour, match data	DT, Random Tree, XGBoost	Supervised Learning	Python, XGBoost, Scikit-learn
Summerville et al. (2021)	DotA 2	Hero picks and bans during the drafting phase, player team roles, historical match outcomes	BN, LSTM	Supervised	Torch, Python
Vardal et al. (2022)	DotA 2	Hero picks and bans during the drafting phase	BN, LSTM, RNN	Supervised Learning	Torch, GeNIe & SMILE
Wang et al. (2018)	DotA 2	17 features including hero damage, tower damage, gold per minute, experience per minute, winning probability	LR, RF, SVM	Supervised Learning	Scikit-learn, Python
Wei et al. (2022)	Honor of Kings	Observation, Action, Reward, State, Skill, Opponent Hero, Target Hero	Proximal Policy Optimization (PPO), DQN	Reinforcement Learning	Python-based interface
Wong et al. (2022)	DotA 2	Hero selection, First Blood	NB, LR, k-NN, SVM, Kernel SVM, NN	Supervised Learning	Python
Ye et al. (2022)	Honor of Kings	Macro-strategy (where to go), Micromanagement (what to do)	CNN	Supervised Learning	Python
Zhang (2021)	Honor of Kings	Push-Turret, Combat, Lane-Farm, Jungle-Farm, Return, Navigation	Multimodal and Multitask NN	Supervised Learning	Python, NumPy, C++ (highly optimised code)

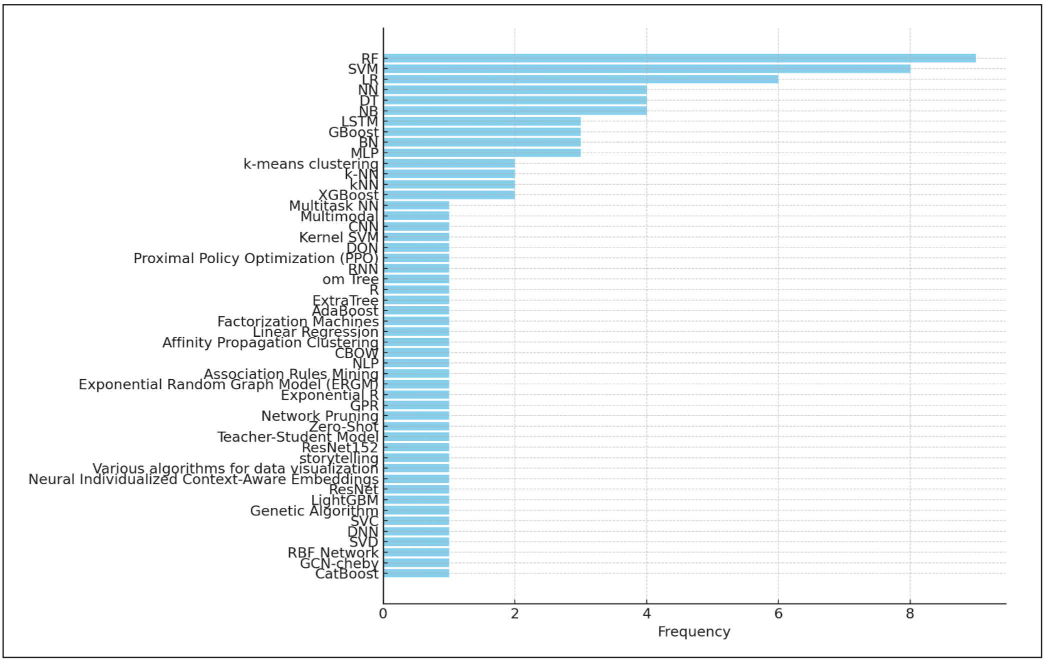

Figure 3. The frequency of each algorithm used in the 35 studies

Results of Individual Studies

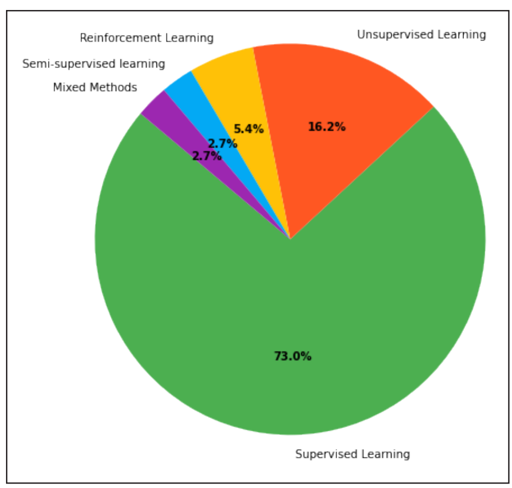

Figure 4. ML algorithm classes obtained from the included studies

Table 4 shows the results of individual studies included in this systematic review, including the findings, reported limitations, and future areas of work if the authors and researchers provide any. The data extracted in Table 4 is to answer RQ2. The studies included in this review mostly aimed to predict the winning team in MOBA games using various predictors. The challenge was to achieve the best prediction results using as few datasets as possible. MOBA games involve numerous players and massive amounts of data, including game environment factors, player actions, opponent actions, and decision-making processes. Developing effective predictors requires deep knowledge and experience of the game, as well as a hypothesis-driven approach. Some studies focused on testing and improving ML algorithms, while others investigated the effectiveness of certain predictors for accurate predictions. One

Table 4
Results of individual studies (findings, limitations, and future area)

Authors (year)	Findings	Limitations	Future area
Bahrololloomi et al. (2023)	GradB model gave the best results in stability and accuracy	Not specified.	Not specified.
Bisberg & Ferrara (2022)	GCN models outperformed traditional ML models; GCN-cheby with delta features, a convolution layer, had the best accuracy	It only includes regular-season games and focuses on league structure, not individual team skill changes.	Use heterogeneous and directed GCN models; Apply models to other esports and sports with similar structures
Canossa et al. (2021)	Detected toxic behaviour patterns using selected game features	The dataset is proprietary and cannot be shared publicly	Explore other genres and apply methods to detect positive player behaviours
Costa et al. (2021)	The most important predictors were player statistics (win rate and KDA); banned champions were less impactful	The study only focuses on pre-game information and does not include in-game dynamics	Future work should explore real-time data and additional feature engineering
Da Silva et al. (2017)	The Multilayer Perceptron achieved the highest accuracy for user identification using gaming biometric data	The study was limited by the small sample size and lack of real-time data	Future work should explore early, mid, and late-game phases separately to account for role changes
Do et al. (2020)	Players preferred recommendations from the system over random selections; CMP effectively captured player preferences	Limited by the availability of public data from Riot Games; challenges with popularity bias	Tune SVD model parameters for improved accuracy; explore real-time and more diverse player data
Do et al. (2021)	Player-champion experience was a strong predictor of match outcomes, with DNN achieving the highest accuracy	Limited to data from the North American server and focused on ranks Iron to Diamond	Future work could explore other regional servers and investigate the impact of player role experience
Edge (2013)	The study successfully predicts player churn in DotA 2 using empowerment and performance metrics; players are more likely to leave when performing poorly relative to their team and opponents	The model only uses end-of-game statistics and lacks real-time data	Future work should include event logs and consider player habits to improve prediction accuracy.
Franco et al. (2019)	Proposed a new metric (GDM) that better differentiates player profiles compared to KDA	Focused on a dataset of professional players only; limited generalisability to casual players	Extend the GDM approach to other e-sports games; involve real players in evaluating the new metric
Guzmán & Medina (2021)	Identified key independent variables for training ML models in MOBA games, with NN being the most effective	Some variables are game-specific and may not generalise well across different games	Focus on optimising variable selection and account for game updates

Table 4 *(continue)*

Authors (year)	Findings	Limitations	Future area
Hodge et al. (2021)	RF accuracy increases until mid-game and then declines, key prediction features evolve over time	Long matches are less predictable, with accuracy dropping in late-game stages.	Improve real-time prediction accuracy and explore other feature selection methods
Hong & Lee (2022)	The system detects in-game events without game APIs, demonstrating robust performance in live-streaming scenarios	Limited to predefined events and game objects, it may not capture all possible in-game scenarios	Extend the detection system to other game genres like FPS and RTS; improve detection of additional event types
Jiang et al. (2020)	The NICE model significantly improves prediction accuracy by incorporating individualised contextual factors	The model was tested on data from a specific period, which may not generalise to other timeframes or game versions	Extend the model to other games and apply it to different types of contextual data
Kim et al. (2020)	The proposed method achieved the best calibration among compared methods, reducing errors	The method was only tested on a limited set of matches, and its performance may vary across different datasets	Expand to other game genres and explore the impact of varying input features on calibration accuracy
Kokkinakis et al. (2020)	The Weavr app enhanced viewer engagement by offering data-driven insights and real-time interactive content	The app was limited to specific in-game events and was tested only on DotA 2 tournaments	Expanding the system to other esports titles and integrating more comprehensive data feature
Liang (2021)	SVM with linear kernel achieved better game outcome prediction compared to DT	Limited by low dimensionality of data with only 38 features; performance may vary with more complex feature sets	Include more features like hero combinations, player skills, and real-time event data to improve prediction accuracy
Luo et al. (2019)	Teacher-student approach reduces training time while maintaining accuracy; Zero-shot approach compromises accuracy for speed; Network pruning cuts down memory usage without significant accuracy loss.	Limited to specific in-game events; computational improvements might not scale to other game genres with different visual aesthetics	Apply methods to more diverse game genres and explore alternative architectures for further optimisation.
Lyu et al. (2022)	GPR achieved the best prediction accuracy, indicating stable performance for predicting risk propensity	Limited to DotA 2; did not include linguistic features or other potential variables	Incorporate linguistic features, expand to other games, explore feature similarity across models
Marchenko & Suschevskiy (2018)	Found that regional affiliation, participation in major tournaments, and team organisation significantly influence player transfers	Limited to transfers between 2016-2017; did not differentiate between voluntary and forced transfers	Explore different types of mobility and develop qualitative methods such as player interviews to better understand transfer reasons

Table 4 *(continue)*

Authors (year)	Findings	Limitations	Future area
Martens et al. (2015)	Detected toxicity through chat analysis using NLP, showing that toxic behaviour is linked to lower chances of game success	Limited to textual data from chat logs, ignoring other forms of communication like voice chat	Expand to other MOBAs and include voice communication analysis for comprehensive toxicity detection
Mohammed et al. (2022)	The draft recommendation system suggests the best heroes for the last pick, enhancing the team to counter opponents	Limited to DotA 2 and only considers predefined scenarios; accuracy is affected by game updates and new patches	Extend to other MOBA games and refine models to adapt to frequent game updates and meta shifts
Mora-Cantallops & Sicilia (2018)	Identified four player types based on social interaction in games, ranging from solo to team players	Limited to structural network data, no demographic or personal player data included	Incorporate demographic data to enhance understanding of player behaviours and social dynamics
do Nascimento Junior et al. (2017)	Identified 7 distinct team profiles, revealing patterns of successful and unsuccessful teams based on performance metrics	Limited to static, end-of-game performance data; did not include dynamic in-game behaviour changes	Extend analysis to include time-dependent statistics and explore other MOBA games.
Porokhnenko et al. (2019)	A linear regression model was the fastest and most suitable for practical implementation; SVM and neural networks provided high accuracy.	Focused on hero picks without considering other in-game factors; results may vary with different datasets and hyperparameters	Explore other game-related factors and optimise hyperparameters to improve prediction accuracy
Prakannoppakun & Sinthupinyo (2016)	Neural Network-based skill rating method outperformed traditional Elo rating by better measuring individual contributions to match outcomes.	Limited by static data from completed games; only considered attributes of selected heroes, ignoring team dynamics and communication	Expand to include real-time analysis and other aspects like player behaviours, communication, and team dynamics.
Semenov et al. (2017)	Factorisation Machines provided the best results for predicting game outcomes, showing effectiveness in modelling hero interactions	The study focused only on hero drafts, excluding real-time in-game factors and other team dynamics	Incorporate real-time data and expand the model to other MOBA games to improve predictive power
Shen (2022)	A Voting Classifier combining the best-performing models achieved good prediction accuracy	Limited to early-game data; does not account for late-game dynamics or champion-specific details	Explore the use of real-time data from different game phases, expand to other MOBA game
Stanlly et al. (2022)	XGBoost achieved the best performance, indicating item and hero choices significantly impact match outcomes	Focused on static in-game data; dynamic player decisions during the match were not considered	Integrate real-time decision-making models and expand to other esports games.

Table 4 *(continue)*

Authors (year)	Findings	Limitations	Future area
Summerville et al. (2021)	LSTM performed best in predicting draft picks, with higher accuracy in the later stages of the draft compared to Bayes Nets	Limited to historical match data from professional games, which may not generalise to other contexts or amateur play	Incorporate amateur match data and adapt models for changing game patches and evolving strategies
Vardal et al. (2022)	LSTM models outperform Bayesian networks, predicting draft choices with good accuracy	Limited data due to professional match focus; only 1518 matches were analysed, which may not generalise across patches	Incorporate data from more patches and explore deeper history in drafting for more complex pattern recognition.
Wang et al. (2018)	A new feature extraction method improved prediction accuracy, showing that detailed hero features enhance outcome prediction	Limited to high-level matches; does not consider dynamic in-game interactions or player-specific strategies	Extend feature extraction to include more in-game variables and test across different MOBA games.
Wei et al. (2022)	RL methods face challenges in generalisation across different heroes and opponents	Existing RL methods struggle with transferability across tasks in competitive settings.	Future work involves enhancing RL model generalisation and transferability across different tasks.
Wong et al. (2022)	Prediction of first blood and match outcome; first blood is not a strong predictor of match outcome	First blood does not add significant predictive power for match outcome	Future work will include hyperparameter tuning, different data encoding, and exploring other classifiers like DT and RF
Ye et al. (2022)	JueWu-SL AI performs at the human level, achieving a high win rate against top human players	AI struggles with Jungle invasion strategy and fast adaptation to opponent's tactics	Future work involves combining Supervised Learning with Reinforcement Learning to improve adaptability
Zhang (2021)	AI achieves human-level performance, handling complex macro-strategy and micromanagement tasks	The AI struggles with the Jungle invasion strategy and fast adaptation	Future work includes enhancing adaptability using Reinforcement Learning

study even developed an AI system to play the game and tested it against real matches and professional players.

Despite their achievements, the studies reported several limitations, such as the need for greater resources for more accurate predictions, algorithm complexity, and multi-step approaches. Some studies used restricted data sources due to gameplay differences among players from different regions. Other studies faced challenges in accessing certain types of data due to game developers' policies and terms and conditions. The studies later identified potential areas for further investigation by future researchers. Those experimenting with predictors suggested adding more predictors, applying more models, and designing a recommendation system for professional teams and organisations. Those working on improving ML algorithms suggested exploring different approaches to the improved method and using more data in future models. These findings can help guide future research in MOBA esports prediction and can benefit the esports community.

Table 5 presents the metrics of ML performance proposed in the included studies, which provide insights for answering RQ3. The proposed ML approaches were assessed using accuracy, precision-recall, cross-validation, and AUC-ROC. The reported performance percentages ranged from 10% to 80% and were deemed impressive, given the simplicity of the datasets used. Such predictions are highly valuable for organisations seeking to simulate or analyse future improvements. Most studies that aimed to enhance ML algorithms reported significant improvements and more than satisfactory results despite an increase in computing resources required and hold promise for future research.

Table 5
Results of individual studies (metrics of ML performance)

Authors (year)	ML metrics
Bahrololloomi et al. (2023)	Accuracy: 92.78%, R^2: 0.8327
Bisberg & Ferrara (2022)	GCN-cheby (1 layer) accuracy: 61.9%; RF accuracy: 57.8%; SCOPE accuracy: 59.7%
Canossa et al. (2021)	Accuracy: High precision with RF and SVM
Costa et al. (2021)	AUC of 0.97 for RF and LR
Da Silva et al. (2017)	MLP accuracy: 86.27% (5 min interval); Bayesian Network accuracy: 75.55% (3 min interval); RBF Network accuracy: 76.1% (3 min interval)
Do et al. (2020)	System recommendations rated higher than random: mean score 6.46 vs. 5.18, $p = 0.01257$
Do et al. (2021)	DNN accuracy: 75.1%; GBOOST accuracy: 75.4%; RF accuracy: 74.7%; SVC accuracy: 74.3%; kNN accuracy: 72.7%
Edge (2013)	NB: sensitivity 70.5%, specificity 67.8%
Franco et al. (2019)	GDM better discriminate player profiles than KDA, with clusters validated by silhouette scores
Guzmán & Medina (2021)	Emphasis was on identifying relevant variables rather than specific accuracy metrics.

Table 5 *(continue)*

Authors (year)	ML metrics
Hodge et al. (2021)	RF accuracy varies, peaking mid-game and declining afterwards
Hong & Lee (2022)	Achieved event detection accuracy with minimal missed events at optimal parameter settings
Jiang et al. (2020)	The NICE model outperformed baseline models with an AUC of 0.953 for predicting match outcomes
Kim et al. (2020)	Achieved accuracy: 73.81%; ECE: 0.57%; MCE: 1.26%
Kokkinakis et al. (2020)	High user engagement during live matches
Liang (2021)	SVM (linear) accuracy: 73%; SVM accuracy: 72.8%; DT accuracy: 68.6%
Luo et al. (2019)	The teacher-student-student approach achieved 99.8% test the curacy; the standard ResNet152 model achieved 94.6% a, with curacy; significant reduction in training and execution time with optimised approaches.
Lyu et al. (2022)	GPR: RMSE = 1.10, R^2 = 0.17; RF: RMSE = 1.20, R^2 = 0.01.
Marchenko & Suschevskiy (2018)	ERGM results showed a significant influence of region and major tournament participation on transfers; association rules highlighted differences between captains and non-captains
Martens et al. (2015)	SVM classification accuracy varied based on the features used; specific numerical metrics were not provided
Mohammed et al. (2022)	Achieved high accuracy in recommending heroes that align with team strategies; specific numerical metrics not provided
Mora-Cantallops & Sicilia (2018)	No specific metrics for ML performance; it focuses on clustering based on network structure.
do Nascimento Junior et al. (2017)	Clustering achieved a significant reduction in data variability, with certain profiles showing high win rates
Porokhnenko et al. (2019)	Linear Regression and SVM achieved an AUC of 0.7739; neural networks showed similar performance with optimised hyperparameters.
Prakannoppakun & Sinthupinyo (2016)	Improved accuracy in predicting match outcomes compared to Elo Rating; specific numerical metrics not provided
Semenov et al. (2017)	Factorization Machines achieved the highest AUC: 0.706 for normal skill level, 0.670 for high skill level, and 0.660 for very high skill level.
Shen (2022)	Voting Classifier accuracy: 72.68%; individual model performances varied but were generally lower
Stanlly et al. (2022)	XGBoost accuracy: 93%; DT accuracy: 82%; RF accuracy: 91%
Summerville et al. (2021)	LSTM achieved 11.94% accuracy in hero prediction, outperforming Bayes Nets and human analysts in strict predictions
Vardal et al. (2022)	LSTM accuracy: 11.94%; Bayes Nets accuracy: up to 11.48%
Wang et al. (2018)	LR: Accuracy improved to 63.8%, SVM: Accuracy improved to 64.3%
Wei et al. (2022)	Win rate: 90% for Diaochan vs. Diaochan, drops when the opponent or target changes; Reward and Elo score provided in specific cases
Wong et al. (2022)	Accuracy: 57%–59%, precision, recall, F1-score
Ye et al. (2022)	Win rate: 86%–100% against various baselines, matches against top human players: AI won 7 out of 10 matches
Zhang (2021)	Win rate: 86%–100%, AI won 7 out of 10 matches against human

Figure 5 displays the percentage distribution of different ML algorithm challenges reported by the studies. The key challenges revolve around the following issues. Overfitting and underfitting hinder model reliability, especially in high-dimensional or imbalanced datasets, affecting predictive power. Generalizability is impacted by constraints in data representativeness, timeframes, and specific game contexts, making it difficult for models to adapt to varied environments. Data is often limited due to privacy concerns or limited feature availability, while high computational demands and model complexity present resource-related constraints. Interpretability challenges arise in unsupervised models and high-dimensional data, limiting insight into model outputs. Scalability issues restrict model application across broader datasets or different games while maintaining predictive accuracy, which is challenging in prolonged, dynamic gaming environments. These challenges underscore the need for tailored ML approaches that address these constraints in data-driven research for gaming and esports applications.

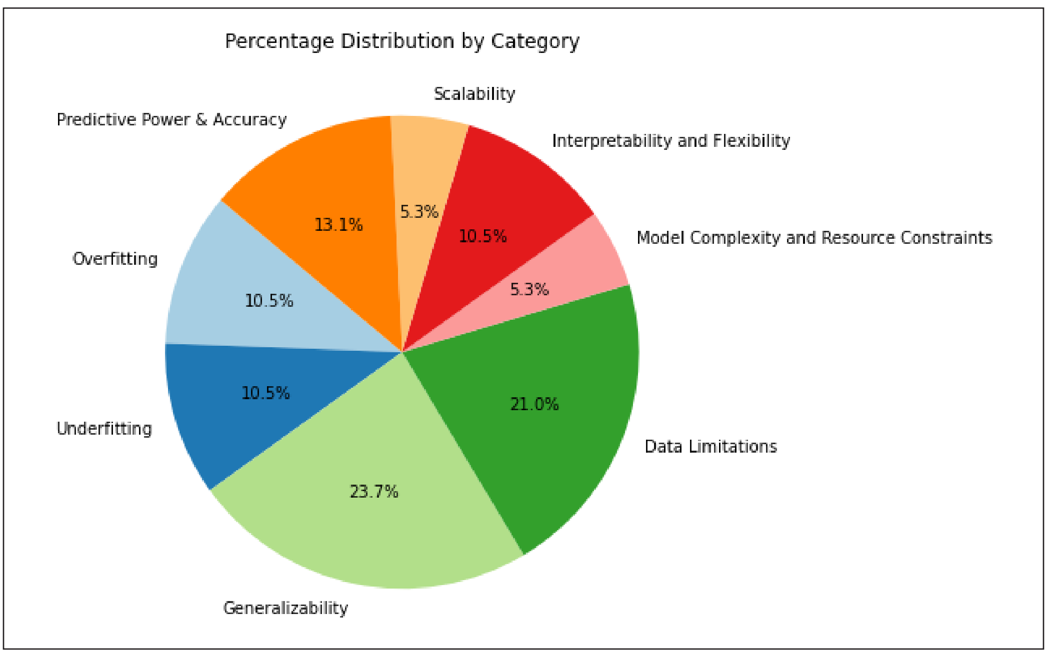

Figure 5. Challenges for ML algorithms deployed in the included studies

Risk of Bias Assessment

Figure 6 shows the risk of bias assessment results for the 35 included studies using PROBAST. All the included studies were assessed to have “low risk” across all domains, indicating reliability and robust methodologies. The participant selection, predictor measurement, outcome assessment, and analytical methods are appropriate and free from significant bias. Their findings can be considered reliable and valuable contributions to

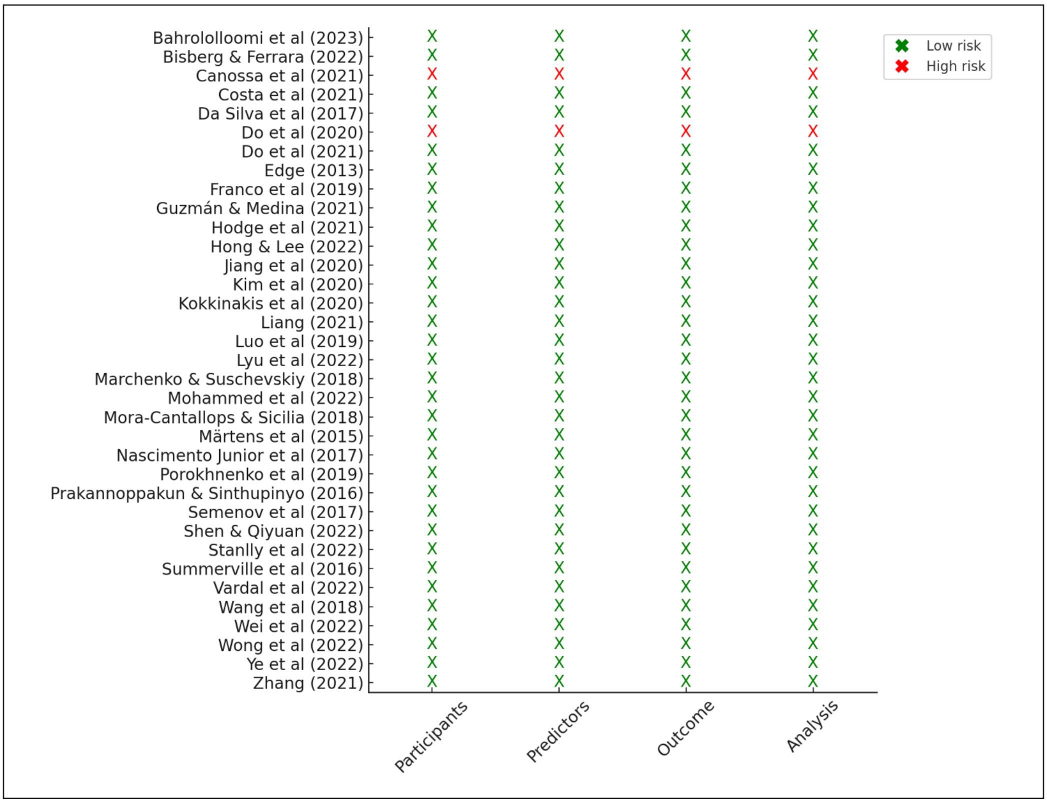

Figure 6. Risk of bias assessment results for the 35 included studies

respective fields. This reliability is crucial for advancing knowledge in the areas of MOBA game analytics and esports research, mostly focusing on DotA 2 and LoL using advanced ML techniques for predictive analysis. The methodologies and ML models used are sound, showing the value of the studies as resources for further research and practical applications in esports. Since these studies show a high standard of research quality, future studies can build upon these findings with confidence, with similar methodologies that could be applied or adapted for future research to continue producing high-quality results.

Results of Syntheses

Figure 7 shows the mean accuracy of different ML algorithms from the studies which reported the accuracy of models' performance. Figure 8 shows the distribution of the accuracy values from the ML algorithms. Among the algorithms with available accuracy data, XGBoost showed high performance with an accuracy of 92.78% in Bahrololloomi et al. (2023) and 93% in Stanlly et al. (2022), indicating its effectiveness in scenarios involving structured data with complex interactions. RF is frequently used and has shown strong performance with accuracies of around 97% (Costa et al., 2021), suggesting that

RF is a reliable choice for handling datasets with numerous predictors. Deep NN also showed high performance, with an accuracy of 75.1%, as reported by Do et al. (2021). This performance reflects the capability of DNNs to capture complex patterns and interactions in player behaviours and game dynamics. SVM models displayed moderate performance, with accuracies of around 73% (Liang, 2021). SVMs are effective for binary classification tasks and are suitable for smaller datasets where feature space dimensionality is manageable. Both k-NN and NB had relatively lower performance in comparison to others, with accuracies

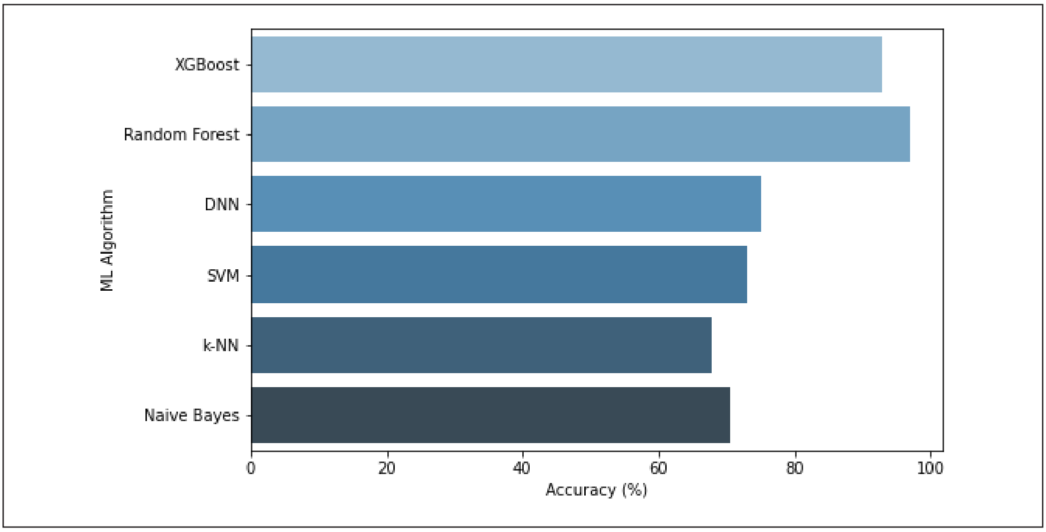

Figure 7. The mean accuracy of different ML algorithms reported in the included studies

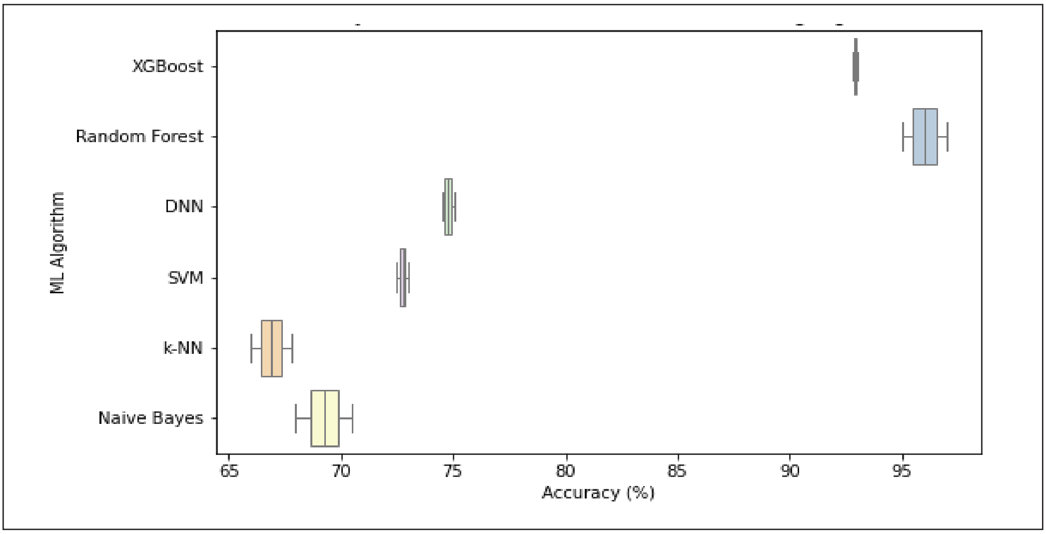

Figure 8. Accuracy distribution of different ML algorithms from the included studies

around 67.8% (Edge, 2013), as they are considered simple models and may not capture complex patterns as effectively as ensemble methods or NN.

Various features encircling MOBA games and esports have been used as predictors in ML modelling. From the 35 included studies, there are four main categories, including player performance and statistics (*n* = 11), in-game events and match statistics (*n* = 7), game mechanics and interaction (*n* = 7), and player behaviour and communication (*n* = 3), with only a study did not have any dataset in their work (*n* = 1), as shown in Figure 9. The highest category shows that a significant focus of the studies is on player-related metrics such as experience points, kill/death ratios (KDA), player statistics, and overall game performance, as the understanding of individual player contributions and behaviours is a crucial aspect in ML modelling given that player performance directly affects game outcomes. In-game events form the second most emphasised category, such as hero kills, tower destruction, and match outcomes, with features that provide insights into how specific in-game events affect the outcome of a match. This highlights the dynamic nature of MOBA, where real-time events play a significant role in match progression. Incorporating these features allows ML models to account for the ever-changing nature of gameplay. The third category (game

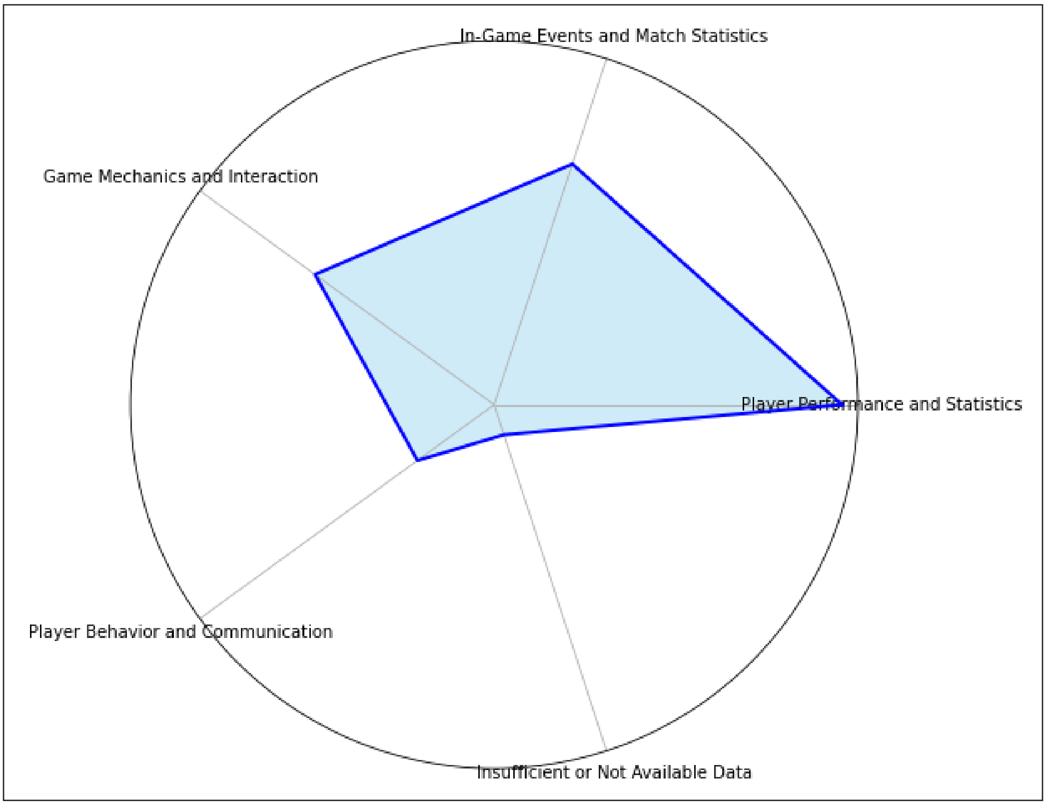

Figure 9. Distribution of predictors' categories used in the included studies

mechanics and interaction) encompasses features like keystrokes, character picks and bans, and team strategies. This reflects the studies' interest in understanding how the mechanics of the game itself affect overall performance. As the interactions between players and game mechanics directly are important, this category is vital for models aiming to simulate match dynamics. This emphasises how player decisions and interactions with game mechanics contribute to the complexity of MOBA games. The least represented category focuses on player behaviour patterns and communication (chat logs), which is less emphasised in current predictive modelling, potentially due to the challenges in quantifying these aspects or their less direct impact on match outcomes.

The distribution of player skill levels used as data in the ML studies is shown in Figure 10. A considerable number of studies in MOBA esports focus on high-level and professional players. This trend suggests that researchers prioritise understanding patterns of elite players, who are often seen as benchmarks for game mastery, as professional players represent the highest skill level and typically have access to more advanced strategies and gameplay. Analysing their data provides valuable information in optimising ML models and AI agents to mimic or counter against top-tier playstyles. The mixed or varying skill levels reflect the recognition that player performance differs widely across skill levels, from beginner to advanced. Including players of varying skill levels allows researchers to develop more generalisable models. This indicates a desire to build models that adapt to different gameplay styles, making the findings more applicable to the average player. While smaller, the advanced/human skill level highlights an interest in comparing ML or AI performance against human capabilities. As AI systems continue to evolve, the

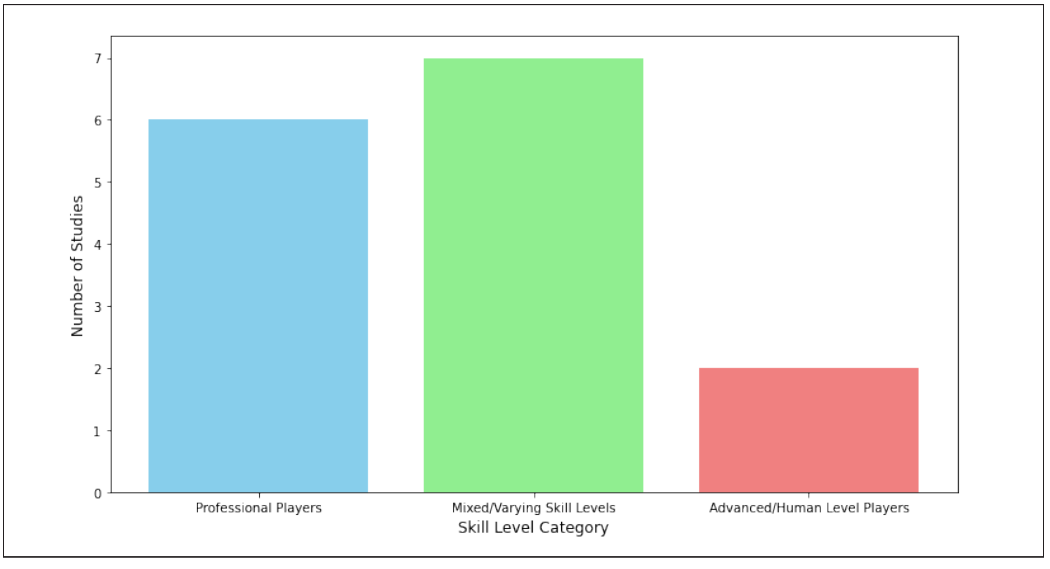

Figure 10. Distribution of the target player skills levels in the included studies

comparison with human-level skills serves as a benchmark for how AI can surpass human capabilities in certain areas.

Figure 11 shows the distribution of included studies based on the dataset regions. The analysis shows that most of the studies focus on data from CN (17.65%) and NA (11.76%). This indicates that the research in MOBA esports is primarily centred around regions with a significant presence in esports. These findings may not fully represent player behaviours or dynamics in other less-studied regions. A considerable number of studies (20.59%) did not specify their dataset region, reducing the transparency of the findings. This scarcity makes it difficult to assess regional diversity and limits the ability to understand regional influence. Several studies (11.76%) have global or international focus, indicating efforts to analyse MOBA esports from a broader perspective. These studies likely offer insights that are more generalised but may still have minute-overlooked differences in a global analysis. Asia (South Korea, Thailand, Indonesia), the EU (United Kingdom), and SA (Brazil) have very few studies (around 2.94% each). Despite South Korea being a major esports hub, it appears to be underrepresented in the dataset. More comprehensive research in diverse regions is needed.

Figure 12 shows the frequency of included studies based on their automation level. High automation is characterised by its ability to handle complex data structures and advanced algorithms with minimal human intervention after the initial setup. These systems excel in efficiency, accuracy, and scalability, making them ideal for real-time data processing and large-scale analytics in dynamic environments like MOBA esports. Lower automation involves a significant increase in human involvement in tasks such as data preparation, model training, and evaluation, often employing simpler techniques (collaborative filtering

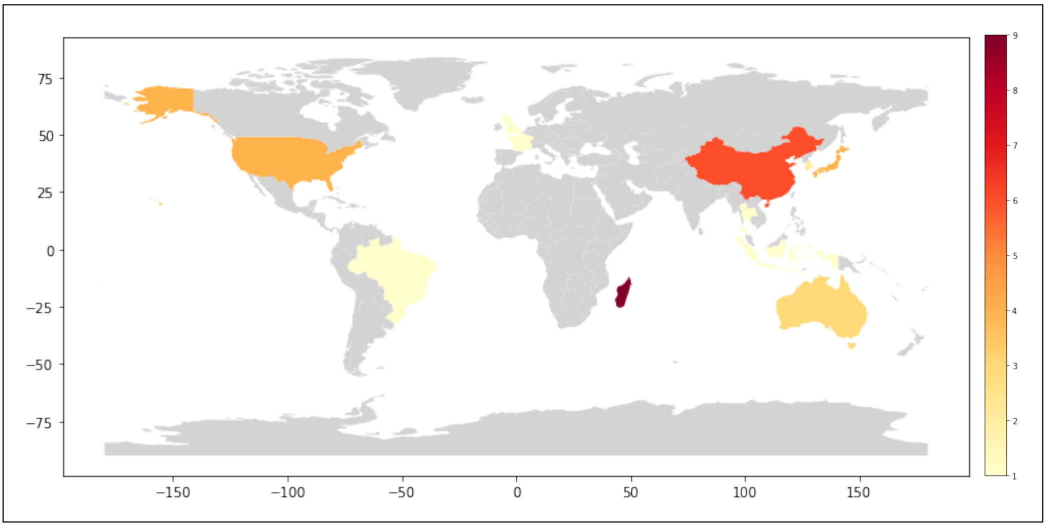

Figure 11. The distribution of the included studies based on dataset regions

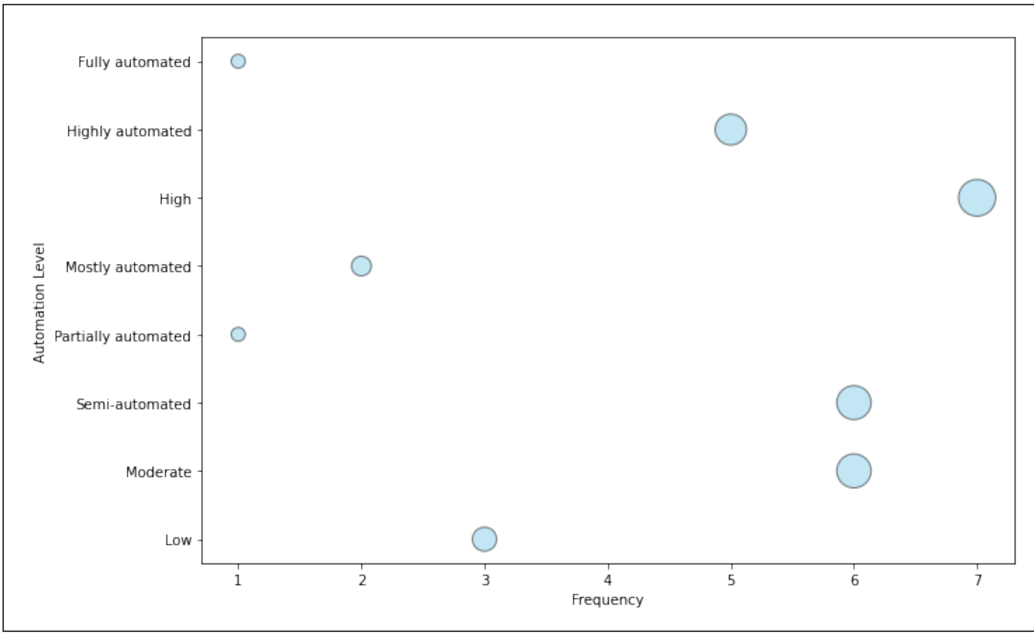

Figure 12. The frequency of studies by automation level

and basic reinforcement learning). Low automation offers flexibility and allows for domain-specific adjustments, but it is more time-consuming, less adaptable to changing data patterns, and limited in scalability.

General Interpretation of Results

This systematic review represents the first attempt to comprehensively explore the use of ML approaches in esports, with a focus on the MOBA genre. Following a rigorous screening process, 35 studies were deemed eligible for inclusion in the subsequent data extraction phase.

Why DotA 2 and LoL?

Both these games are popular in ML research because they provide a rich and complex environment for studying artificial intelligence and decision-making (Guzmán & Medina, 2021; Summerville et al., 2021). Both games involve real-time strategy, and players need to make decisions quickly and adapt to changing circumstances to win. DotA 2 and LoL have been used as testbeds for studying multi-agent systems and reinforcement learning (Du et al., 2021). Each player controls a character (or "hero") in these games and must work with their team to defeat the opposing team. This creates a complex environment with many interacting agents, making it an ideal setting for studying multi-agent coordination and cooperation. Moreover, both games provide large and publicly available gameplay datasets, allowing researchers to train and evaluate ML algorithms on authentic data. This has led to the development of advanced AI systems for playing DotA 2 and LoL, which can compete at a prominent level against human players (Berner et al., 2019). Overall, DotA 2 and LoL are popular in ML research because they provide a challenging and realistic environment for studying AI and decision-making, as well as rich datasets for training and evaluating ML approaches.

PC and Mobile Phone MOBA

DotA 2 and LoL are some examples of computer-based MOBA. Other than PC, mobile phone MOBA has grown in popularity in recent years, with games such as Arena of Valor (AoV), Mobile Legends: Bang Bang (MLBB), and HoK leading the way (Yang et al., 2022). These games are especially popular in the Southeast Asia region, with a massive player base and even professional esports leagues (Ong et al., 2023). According to a report by market research firm Newzoo, mobile MOBA generated $15.3 billion in revenue in 2020, the most profitable genre in mobile gaming. The report also stated that mobile MOBA has over 628 million players worldwide, with most coming from China and Southeast Asia. Surprisingly, despite its popularity, research in this part is still very scarce.

Recommendation Systems

ML can be utilised to develop recommendation systems for MOBA esports, helping players make informed decisions about their gameplay strategies. The studies have shown that ML algorithms can analyse a player's gameplay data (Maymin, 2021), such as their win-loss record (Porokhnenko et al., 2019), character selection (Chan et al., 2020), and in-game performance (Hodge et al., 2021), to predict favourable outcomes. However, studies have also identified challenges in implementing this approach for end-users. Despite the challenges, the benefits of ML for recommendation systems in MOBA are significant. For example, ML can provide improved personalisation and real-time recommendations during matches, enhancing player engagement and retention. Additionally, ML can help game developers identify balance issues and make data-driven changes to improve the overall gaming experience (Kokkinakis et al., 2020). Overall, ML-based recommendation systems offer numerous benefits to MOBA esports.

Real-time Decision-making

An emerging area with significant potential is the use of ML models for real-time decision-making during live esports matches. In fast-paced games like MOBA esports, ML models have the potential to offer actionable insights that can be used by players and coaches, such as optimal hero selections or item builds based on the current state of the game. ML algorithms could dynamically analyse player and team performance, map control, and resource management to generate recommendations in real-time. Another promising application is an AI-powered coach that can provide players with feedback on their performance during games by identifying patterns in their gameplay and suggesting real-time improvements to help players adjust their tactics, making them more adaptable. However, integrating ML into live esports matches may pose unique challenges. Real-time models need to process large volumes of data with minimal latency to ensure that decisions are made quickly enough to be useful. Furthermore, the deployment of ML-driven decisions in real-time raises ethical and fairness considerations, particularly if certain teams or players have access to superior analytical tools that could create an imbalance in competitive play.

Data Access Challenges

One of the primary challenges faced by researchers in this field is access to comprehensive and high-quality game data. Game developers often restrict access to data to protect proprietary information, maintain player privacy, and adhere to regional regulations. These restrictions limit the scope of data, introducing biases that affect the generalisability of findings caused by sampling biases, where certain demographics are underrepresented. Additionally, data from publicly available sources or community-collected datasets may not cover all aspects of the game, leading to gaps in understanding player behaviours and game dynamics. Fostering collaborations between researchers and game developers could provide a pathway to better data access. These partnerships could facilitate access to anonymised or aggregated data, balancing the need for privacy with the research community's need for comprehensive datasets. Advocating for open data initiatives within the gaming industry could promote the sharing of data in a controlled and secure environment.

Regional Differences

The gameplay strategies, player behaviours, and game meta can vary significantly across different regions due to cultural influences, regional preferences, and local competitive environments. Players in one region may prefer aggressive strategies (SEA and CIS) and hero selections, while others favour defensive playstyles (EU and CN). These lead to inconsistencies in ML model performance that lack generalizability. This poses a challenge in synthesising results and drawing broad conclusions applicable to the global scene. Future research should aim to include cross-regional studies that compare gameplay and data in a worldwide setting so that researchers can better understand universal versus region-specific insights. Additionally, current research is skewed towards a few prominent regions, CN and NA, with other regions remaining underrepresented or unspecified. Future research should strive for greater inclusivity and transparency in regional data to provide holistic understanding and enhance the applicability of ML across diverse populations.

CONCLUSION

Implication for Future Research

Other than PC esports, there is a need to empower research on mobile phone-based MOBA. The popularity of mobile MOBA can be attributed to their accessibility, as they can be played on a wide range of mobile devices and social aspects, with players being able to team up with friends and participate in global tournaments. Additionally, the fast-paced gameplay and constant updates and events keep players engaged. Mobile phone MOBA often has more diverse player bases and unique game mechanics compared to traditional PC-based MOBA, making them an attractive field of study for researchers. This would have immense potential to gain access to a much bigger data mine for a great prospect on ML-based studies. Researchers might be intrigued by *"How to develop mobile phone-based MOBA ML models for prediction"* or *"What specific challenges and opportunities in using mobile phone-based MOBA data for ML research compared to traditional PC-based MOBA*."

The syntheses of subgroups reflect the complexity of MOBA esports. The insights from most predictors used suggest that researchers prioritise quantifiable and directly impactful features when constructing ML models. There is potential for growth in examining less-explored aspects, such as player communication, teamwork, and leadership, which could enrich predictive analytics. Based on players' skill levels, there is a need to analyse a wider spectrum of skill levels to better understand learning curves, mistakes, and strategies unique to less experienced players. Given the varying skill levels, ML models should be designed to be more adaptive to the provided datasets. In terms of human intervention, high automation could streamline predictive analytics and provide rapid insights, while low automation could enhance understanding in scenarios requiring human analysis. Future research may aim to integrate both approaches for maximum efficiency, leveraging their strengths.

Another broad aspect of implications is to push for the commercialisation potential for ML-based applications that non-researchers like MOBA esports teams and managements can deploy. Players and teams can train effectively by using quantitative and scientific methods to perform analysis and develop decision-support systems. However, providers must take secure measures should commercial products with ML technologies use professional data. ML with the ability to analyse large volumes of game data may commercialise:

1. **Performance analysis application:** An app that highlights strengths, weaknesses, and areas for improvement for individual players and teams, providing detailed feedback on gameplay mechanics (positioning, skill usage, and team coordination) to help players refine their strategies and optimise their in-game decisions based on match reports.
2. **Strategic decision-support system:** A third-party software for commercial use that can act like a virtual coach that provides real-time recommendations during practices, helping teams learn to adapt to changing conditions. This system might

also analyse opponent behaviours, predict future moves, and suggest optimal responses after matches.

3. **Customised training program:** An enhanced match reporting API or web-based system that facilitates personalised training programs by analysing a player's historical performance data and tailoring training routines to address specific weaknesses with automated coaching systems to accelerate target growth area.
4. **Fan engagement and content creation:** Plugins or tooltips in live or video streaming services provide deep insight into professional players' thoughts and actions before, during and after matches for general audiences and players.
5. **Real-time decision-making tool**: Advanced AI systems that support non-players and teams during gameplay enhance competitive performance and viewer engagement. This approach could also open new avenues for the commercialisation of AI tools in esports, making ML-driven decision-making an integral part of competition viewership.

Deploying ML in esports faces several challenges, including data privacy concerns, scalability, and integration with existing infrastructure. However, the success story of DotA 2 OpenAI displayed how AI and ML can benefit the esports industry as a whole (Berner et al., 2019). From a simple project of creating a mode where a team of five humans fight against 5 AI opponents, the DotA 2 community and players (casual and serious) enjoyed the mode and successfully improved their gameplay as AI opponents have very high skill levels. Content creators and professional teams alike produce huge numbers of content and engagement through this mode, showing the significance of AI advancement.

Further, developing robust methodologies for data access restrictions and regional variations is important. Future research should prioritise transparency in data collection methods, clearly outlining any limitations and biases. The development of standardised protocols for data sharing can help mitigate the impact of these challenges for more reliable and generalisable findings. Normalisation techniques might be helpful in standardising data from various regions, making it more comparable and reducing regional biases. Transfer learning could also be employed to improve model applicability for multi-region studies. By addressing these issues, the field of ML applications in MOBA esports can advance, providing insights that are both scientifically rigorous and practically relevant to the global gaming community.

Limitations

Conducting a systematic review for ML in MOBA is challenging due to the small number of studies available, which can limit the scope and generalizability of the findings. This can be because ML is a new field in esports research (Reitman et al., 2020), and MOBA is just one genre of many in esports. There is also a potential for bias or inconsistencies in the methodology or reporting of the studies included in this review, which can affect the accuracy and reliability of the results. The rapid evolution of both the field of ML and the esports industry, too, in general, can mean that the studies included in the review may become outdated quickly. Another limitation of this systematic review is the possibility of missing relevant studies. The search strategy used may not be comprehensive enough to capture all relevant studies, or some studies may be published in non-English language journals and may not be included in the earlier search and screening process. In addition, the studies included in the review may have used different datasets, variables, and ML algorithms, which can make direct comparisons difficult.

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