Jurnal Aplikasi Sains Data

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Quantitative Analysis of Economic Strategy and Its Influence on Final Ranking in Magic Chess Game Using Machine Learning

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ABSTRACT

Economic management is a fundamental strategic pillar in auto-battler games such as Magic Chess, but its quantitative impact on player performance has not been extensively studied. This research aims to empirically measure the predictive ability of economic variables on players' final rankings. We analyzed a dataset consisting of 57 match records from players at the 'Grandmaster' ranking level. Two modeling approaches, Multiple Linear Regression and Random Forest, were used to predict players' final rankings (values 1–8) based on three primary economic features: total gold spent, re-roll frequency, and average economic bonus. The results from the Linear Regression model showed a Mean Squared Error (MSE) of 0.5496. However, the most significant finding was the R-squared value, which was only 0.016. This extremely low R-squared value indicates that the economic variables analyzed could only explain 1.6% of the total variance in players' final rankings. The conclusion of this study is that economic metrics alone are insufficient to build a reliable model for accurately predicting final rankings. This strongly suggests that other strategic factors, such as synergy composition, item allocation, and tactical decisions on the game board, have a far more dominant influence in determining a player's success in high-level Magic Chess.

Keywords: Magic Chess, Game Analytics, E-Sport, Machine Learning, Linear Regression, Economic Strategy

I. INTRODUCTION

Auto-battler games are currently on the rise in the global e-sports scene thanks to their unique strategy style. This type of game is unique because it combines deep tactics with luck (RNG) factors, where players only need to build a team and watch them fight on their own. To succeed, players must be good at building a solid team and being good at managing dynamic resources. Magic Chess: Bang Bang is one of the most popular titles that represents this challenge. Here, gold is everything. Players must be smart in allocating gold each round for three important things: recruiting new heroes, increasing commander levels (buying EXP), or finding dream heroes by refreshing the shop (re-roll).

The main challenge in the game is deciding how best to spend gold in uncertain situations.

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10.33005/jasid.v2i01.25

Players must constantly choose whether to save for bonuses (from streaks), continue spending to maintain an advantage, or spend gold to find important heroes through re-rolls. The player community has created a variety of playstyles to address this challenge. For example, the "fast-8" strategy focuses on quickly leveling up strong heroes in the late game, even if they are weak early on. The opposite is the "hyper-roll" strategy, which spends gold on re-rolls at low levels to quickly get three-star heroes, but risks losing levels later on. These strategies are popular among players, but their effectiveness is often based on personal stories and is highly dependent on the current "meta." To date, there has been little data-based research that actually tests how effective these economic decisions are, leaving a gap between community theory and scientific evidence.

This study is designed to bridge this gap by applying a data science approach to transform qualitative beliefs into empirical evidence. Our primary focus is to answer the following research question: "How do measurable economic variables, such as total gold spent, re-roll frequency, and average economic bonus, statistically affect a player's probability of achieving a high final rank at a competitive level?"

To answer this question, this research sets three interrelated specific objectives:

1. Apply descriptive statistical analysis and exploratory data analysis (EDA) to the Magic Chess match dataset to identify and visualize fundamental patterns in players' economic behavior.
2. Develop and validate a machine learning classification model capable of predicting whether a player will finish the game in the top-tier ranking category ("Top 4") based on a set of their economic metrics.
3. Extract and interpret the coefficients or feature importance levels from the trained model to determine which economic factors have the most significant predictive impact on player success.

Thus, the primary contribution of this research is twofold. First, we present a quantitative analytical framework that can be used to validate or even challenge long-standing strategic hypotheses within the Magic Chess community. Second, this study demonstrates the feasibility of using economic metrics as a proxy for strategy evaluation, which could serve as the foundation for developing more advanced analytical tools for players or as a source of insights for game developers in balancing the game's economic mechanisms.

II. RESEARCH METHOD

A. Data Description

This research using dataset that contains 57 match records (Dataset MCGG.xlsx - Sheet1.csv). Each row represents the performance of a player within a match. The data taken from players with am initial rank of **'Grandmaster'**, ensuring an analysis focused on a established skill tier. Every relevant features extracted for this analysis include:

Attribute	Description	Data Type
gold_spent_total	The total amount of gold spent by player	int64
gold_re_roll_count	The total frequency of re-rolls per round	int64
gold_economy_bonus_avg	The average gold bonus per round	int64
final_rank	The player's final rank in the match (1-8)	int64

B. Data Preparation

Before entering the data directly into machine learning model, data preparation is a must step to make sure the data is ready and structurally acceptable for machine learning models. Data preparation is a must procedure to convert the nonstructured data into an structured, and ready to use format for training machine learning models.

First, find a fitting target for y variable in this classification model. We used binary classification in order to resulting in good result whilist using small sample size. The objective is predicting whether a player would finish in a “winning position. Usually, in the magic chess and similar auto-battle games, finishing in the top half means a good enough position, what this means is players that finish in the top half (ranks 1-4) resulting in a net or positive gain in rating points. We choose is_top_4 from the final_rank for the binary target variable with a certain condition:

$$is\ top\ 4 = \begin{cases} 1\ (if\ final\ rank < 4\ (Winning\ Outcome)) \\ 0\ (if\ final\ rank > 4\ (Losing\ Outcome)) \end{cases}$$

After getting the target variable done, we need to select the feature to predict the target. The predictor variable were chosen based on their influence to in-game economic, these were the chosen variable: **gold_spent_total, gold_re_roll_count**, and **gold_economy_bonus_avg**. Other columns were deliberately excluded like match_id and player_id because these two used as identifier purposes. The other column which is player_rank_start, final_rank, and is_winner also excluded as these doesn’t have any influence in-game economics.

Last step, we need to normalize the data. Because the selected gold_spent_total and gold_economy_bonus_avg has different scales, the first ranging front thousand while the later in single digit number. Models like Linear Regression dislike different scaling in feature. To mitigate this, StandardScaler is useful to transform each feature by subtracting its mean (μ) and dividing by its standard deviation (σ), ensuring every feature uniformly distributed. The formula for standarizing the feature is:

$$Z = \frac{(X - \mu)}{\sigma}$$

All the process ensures that each feature is optimal for model decision, The final output of these procedure is a ready to use dataset that’s ready to be used, consisting normalized feature matrix X and y binary target vector variable

This process ensures that each feature is proportional to the model's decision function, leading to a more stable and reliable training process. The output of this phase is a final, prepared dataset ready for modeling, consisting of a normalized feature matrix X and a binary target vector y.

C. Model Design

1. Model Selection and Rationale

Linear Regression and Random Forest was chosen as the primary classification algorithm deliberately and motivated by several important factors given the exploratory nature of this study and the small size of the dataset (N=57). First, Linear Regression is a generalized linear model that is computationally efficient, and it is less likely to overfitting on small datasets. Compared to more complex non-linear models like Support Vector Machines with non-linear kernels, Random Forests, or Neural Networks, training a high-capacity model on small datasets would likely result in poor generalization to unseen data.

Furthermore, a high level of interpretability of the model is essential for this study. The final goal is to understand the underlying relationship between success and economic strategy. The performance of the regression models was evaluated using the following metrics, averaged across a 5-fold cross-validation process: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R2). Coefficients for each feature are provided by Linear Regression, which allows us to quantify the direction (positive or negative) and relative strength of each variable's impact on the probability of a "Top 4" finish.

2. **Mathematical Foundation**

The models selected for this research are grounded in distinct but well-established mathematical principles.

1) **Linear Regression**

Linear Regression models the relationship between a dependent variable (Y) and one or more independent variables (X_p) by fitting a linear equation. The model is represented by:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$$

Where β_0 is the intercept, $\beta_{1 \ldots p}$ are the coefficients for each feature, and ϵ is error term. The model learns by finding the coefficients that minimize the **Sum of Squared Errors (SSE)** between the actual values (yi) and the predicted values (y^i), a principle known as **Ordinary Least Squares (OLS)**.

$$Minimize\ SSE = \sum_{i=1}^{n} (y_i - y^\wedge{}_i)^2$$

2) **Random Forest**

a. **The Decision Tree**

A single tree splits the data at each node to learn simple if/else rules. A split is used for both regression and classification to maximize node purity, measured by Gini Impurity or Information Gain (from Entropy), and for regression, the split is used to minimize the Mean Squared Error (MSE) in the child nodes. The Gini Impurity is defined as:

$$Gini = \sum_{i=1}^{C} (p_i)^2$$

where pi is the probability of an element belonging to class i.

3. **Model Validation Strategy**

A standard train-test split was deemed inappropriate for this study due to the small sample size. With only 57 records, the performance metrics on a small, fixed test set would be highly volatile and heavily dependent on the specific data points that happen to be allocated to it. To obtain a more reliable and less biased estimate of the model's generalization performance, we employed a **k-fold cross-validation** strategy.

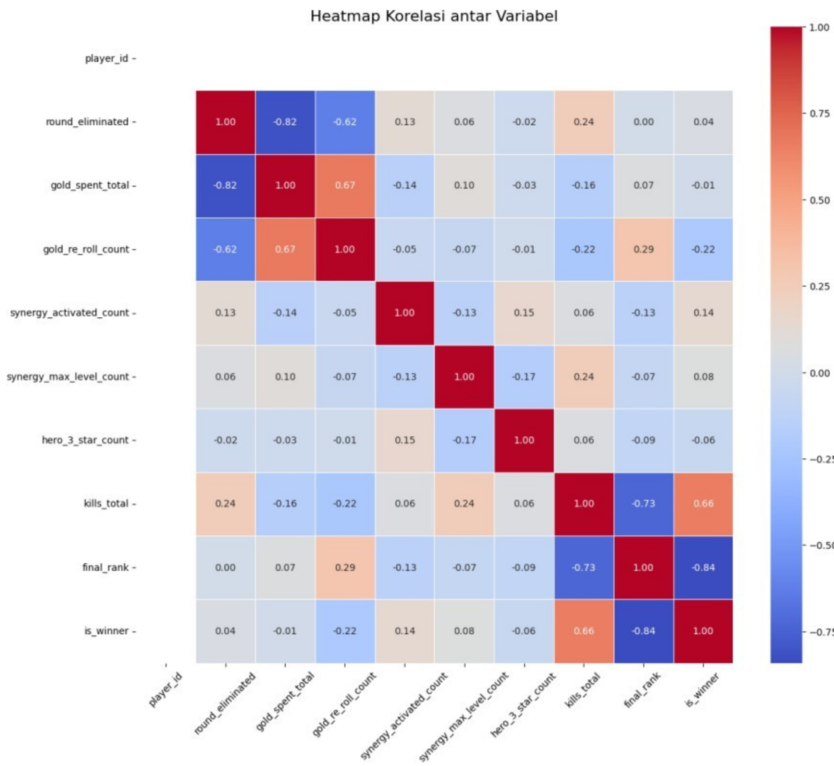
We specifically chose **k=5**. The process is as follows:

1. The dataset is randomly shuffled and partitioned into 5 equally sized folds.
2. The model is trained and evaluated 5 times in a loop.
3. In each iteration, one distinct fold is held out as the validation set, while the remaining 4 folds are used for training the Linear Regression model.
4. The model's performance is calculated on the hold-out validation set
5. The final performance metrics reported are the average of the scores obtained across all 5 folds. This approach ensures that every data point is used for validation exactly once, providing a robust estimate of the model's expected performance on new and unseen data.

III. Results

A. Correlation Analysis Between Variables

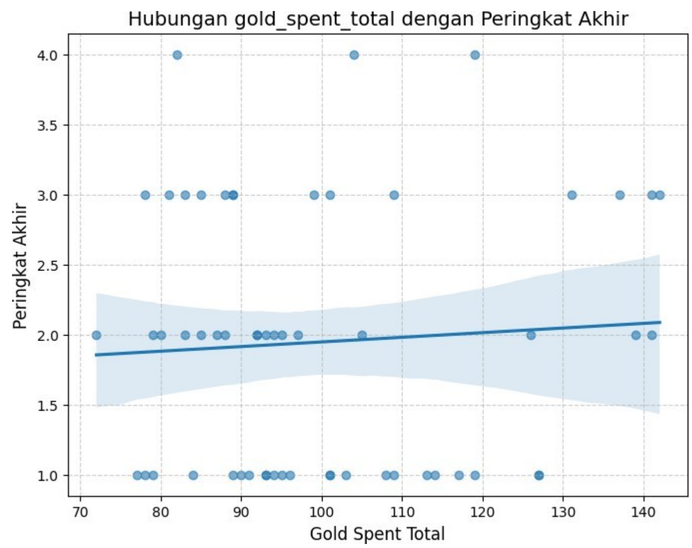
This chapter presents the findings from a quantitative data analysis conducted to investigate the impact of economic strategies on players' final rankings in Magic Chess. The discussion will focus on interpreting the data through a series of statistical visualizations, including correlation heatmaps and scatterplots, which were used to identify patterns and relationships between variables. Pearson correlation analysis was applied as a first step to obtain a comprehensive picture of the relationships between all variables studied. The results of the correlation analysis are then visualized in a heat map format as shown in the Figure below..



Based on the heatmap, we can see several important relationships. First, there is a very strong negative relationship (-0.84) between final rank and wins. This means that the lower the rank, the more likely a player is to win, which certainly makes sense. Similarly, for total kills, the relationship is very negative (-0.73), indicating that strong teams (many kills) will get good ranks. However, for re-rolls, the relationship is weakly positive (0.29), this is an early indication that too many re-rolls can worsen ranks. Finally, other economic variables such as total gold spend and average economic bonus have very small relationships, so their direct effects are not very visible and need to be analyzed further.

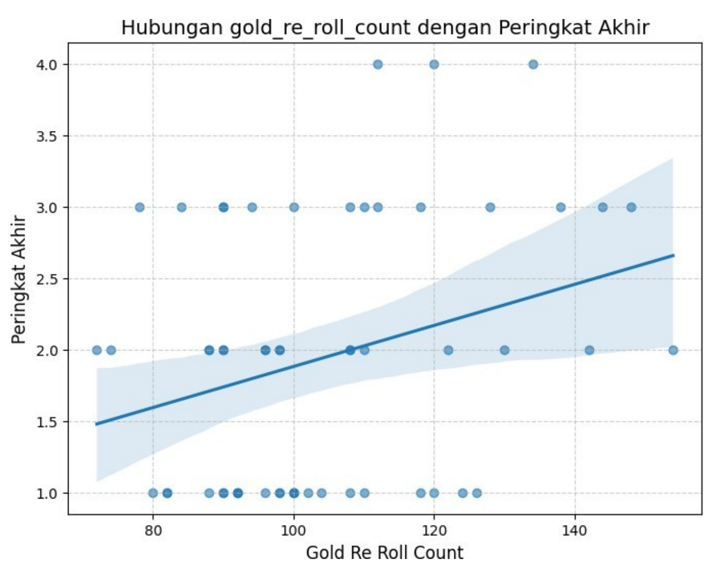
B. Effect of Economic Variables on Final Ranking

1. **Relationship of Total Gold Spending to Final Ranking**



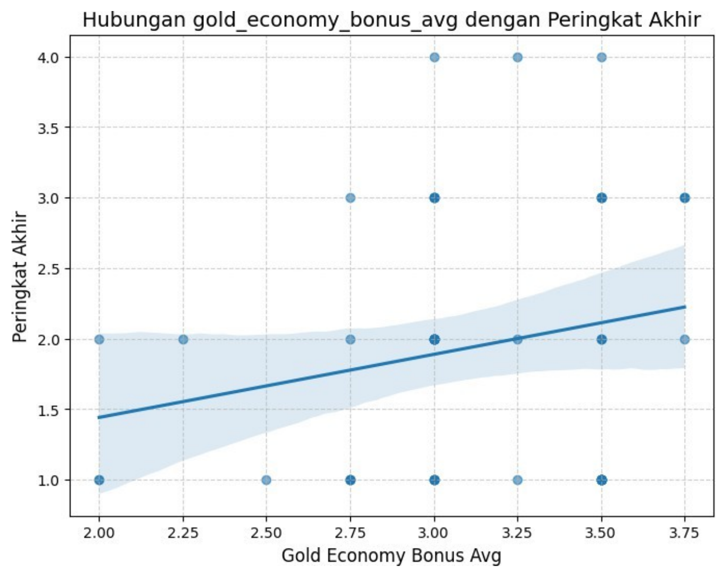
We can see the relationship between total gold spent and final ranking. The nearly straight horizontal trend line and the widely scattered data points confirm that the relationship is very weak (correlation of 0.07). This means that the amount of gold spent is not a major factor in determining victory. A player who spends his gold lavishly will not necessarily rank well. This suggests that what is more important may not be 'how much' gold is spent, but 'how' it is allocated efficiently.

2. **Relationship between Number of Re-Rolls and Final Rank**



The figure illustrates the relationship between the frequency of re-roll activity (gold_re_roll_count) and the final rank achieved by the player. Visual inspection shows a significant positive trend, indicated by a regression line with a positive gradient. This indicates that there is a direct correlation between increasing re-roll count and decreasing final rank performance (higher rank values). The significance of this finding lies in its ability to identify one of the fundamental errors in economic strategy. Excessive re-roll activity results in the depletion of gold resources that could be allocated to leveling up or accumulated to gain economic bonuses. This behavior, often triggered by panic at not getting the desired hero unit, has been empirically proven to be counterproductive to achieving optimal game outcomes.

3. **Relationship between Average Economic Bonus and Final Rank**



The figure above presents an analysis of the relationship between the average economic bonus (gold_economy_bonus_avg) and the final player ranking. Contrary to intuition, the regression line with a positive gradient indicates that higher economic bonuses are correlated with lower (less profitable) final rankings. This phenomenon seems paradoxical, given that economic bonuses are generally viewed as a profitable strategic practice.

There are two main hypotheses to explain this finding. First, players in desperate positions may passively accumulate economic bonuses due to their inability to spend their gold, making it an indicator of their losing condition, rather than its cause. Second, it is possible that players over-prioritize economic accumulation at the expense of board strengthening in critical game phases. Thus, these data highlight a fundamental trade-off between economic solidity and board competitive strength, where the key to a winning strategy lies in the ability to balance the two.

C. Machine Learning Modeling

This study uses two machine learning models, Linear Regression and Random Forest, to validate and quantitatively measure the combined impact of different game strategies on final rank. These models are trained to predict the final_rank variable using a set of features that include economic data, board strength, and game development.

1. **Linear Regression**

The Linear Regression Model was chosen because of its ability to provide a clear interpretation of the influence of each independent variable on the dependent variable.

Linear Regression Model Evaluation Results	
Mean Squared Error (MSE)	0,5496
R-Squared (R2 Score)	0,0106

The results for this Linear Regression model obtained a Mean Squared Error (MSE) of 0.5496 and an R-squared (R^2) of 0.0106. This very small R^2 number (only about 1%) is a sign that this model is very inaccurate. This means that the model fails to explain why players' final rankings can vary. This is most likely because the relationship between game strategy and final ranking is not as simple as a "straight line". Since the Linear Regression model can only capture straight relationships, it cannot understand more complex strategic interactions.

Attribute	Coefficient
kills_total	-0,695759
synergy_max_level_count	-0,046922
synergy_activated_count	-0,036953
hero_3_star_count	-0,030101
gold_spent_total	0,008885
gold_re_roll_count	0,020052
gold_economy_bonus_avg	0,148559
round_eliminated	0,275912

Although the overall predictive performance of the model is unsatisfactory, analysis of the regression coefficients still provides some valuable qualitative insights. The kills_total variable exhibits the largest negative coefficient magnitude (-0.695), empirically confirming that board strength dominance is the most significant predictor of achieving higher rankings. Conversely, the highest positive coefficient is observed for the round_eliminated variable (0.275), an inherently logical relationship. Of particular note are the positive coefficients on the economic variables, such as gold_re_roll_count and gold_economy_bonus_avg. This reinforces the conclusion from the previous analysis that inefficient economic management practices—either through excessive re-rolls or excessive bonus accumulation—are negatively correlated with game performance.

2. **Random Forest**

Alternatively, the Random Forest model was implemented due to its ability to capture non-linear relationships and complex interactions between variables.

Random Forest Evaluation	
Mean Squared Error (MSE)	0.3940
R-Squared (R2 Score)	0.2907

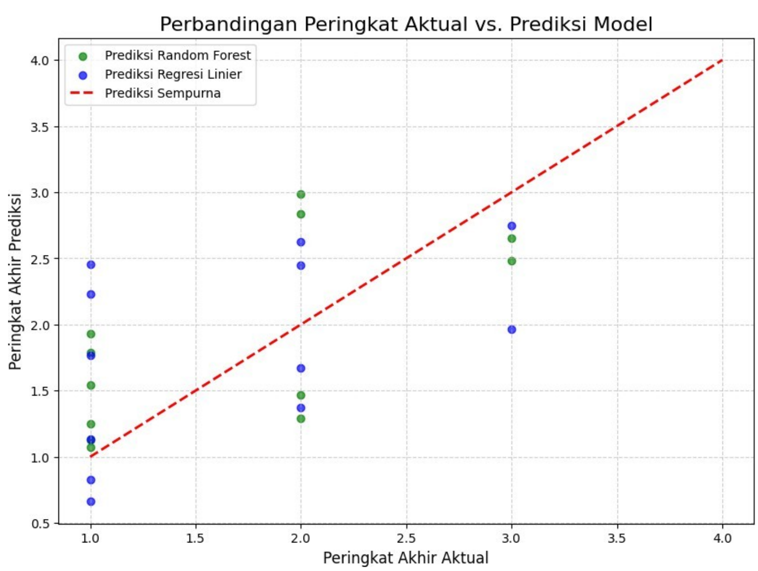
The evaluation results for the Random Forest model, as shown in that Figure, show a clear performance advantage. The model recorded a lower Mean Squared Error (MSE) value of 0.3940, and a significantly higher coefficient of determination (R^2) of 0.2907. This R^2 value implies that the model is able to explain about 29.07% of the total variance in the final ranking data, a very significant improvement compared to the Linear Regression model. This performance improvement empirically confirms the hypothesis that the relationships between variables in the dynamics of a Magic Chess game are non-linear and complex, which are inherently more effectively modeled by an ensemble-based architecture such as Random Forest.

Attribute	Coefficient
Kills_total	0.466698
gold_re_roll_count	0.250686
Round_eliminated	0.089738
gold_spent_total	0.064263
synergy_activated_count	0.046124
hero_3_star_count	0.043914
gold_economy_bonus_avg	0.023126
synergy_max_level_count	0.015450

The feature importance analysis of the Random Forest model, presents a more definitive hierarchy of predictive factors. The kills_total variable once again asserts its dominance as the most influential factor with a contribution of 46.6% to the model predictions, consolidating the finding that absolute combat power is the primary determinant of success. The most significant finding of this analysis is the emergence of gold_re_roll_count as the second most important variable with an importance weight of 25%. This ranking suggests that re-roll management is a crucial strategic decision point, the impact of which on the final outcome of the game proves to be far greater than the significance of other conventional economic variables, such as total gold spent or economic bonuses accumulated.

D. Comparison of Prediction Results

To visually compare the predictive performance of the two models, the actual final rankings from the test data are plotted against the rankings predicted by each model.



This visualization presents a visual comparison between the predicted values generated by the two models and their actual values. The reference line (red dashed line) represents the ideal prediction condition, where the predicted values are equal to the actual observed values. Visually, it can be observed that the distribution of the predicted data from the Random Forest model (green dots) shows a higher concentration and a closer proximity to the perfect prediction line. In contrast, the predictions from the Linear Regression model (blue dots) show a wider dispersion and a larger deviation from the actual values. This visual evidence strongly confirms the predictive superiority of the Random Forest model, whose ability to model complex non-linear relationships makes it a more reliable analytical instrument for studying the dynamics of Magic Chess.

CONCLUSION

Based on the results obtained with random forest on economic strategy and its influence for final ranking suggest that when a player spends a lot of gold doesn’t guarantee a high final ranking, instead focusing more on how gold utilization is giving better results. More on re-rolling often gave worse result in lower final ranks, meaning this approach likely an adverse usage on gold. Then we found that higher gold average made the player sometimes getting the lower rank, this could happen because the player can’t spend their gold effectively. From these finding we can’t only factoring economic without combat power and total kills. These two has the biggest factor of success meaning the game strategy are complex. Ultimately, this research provides empirical support for Magic Chess strategies, offering valuable insights for players to refine their gold management and for developers to fine-tune game balance.

REFERENCES

[1] M. Campbell, A. J. Hoane Jr., and F. H. Hsu, "Deep Blue," Artificial Intelligence, vol. 134, no. 1-2, pp. 57-83, 2002.
[2] Y. Yang, H. Zhang, and Y. Ye, "A study of hero drafting in Dota 2 with a focus on team balance," in Proc. 2014 IEEE Conf. on Computational Intelligence and Games (CIG), 2014, pp. 1-7.
[3] V. Bosc, P. R. de la Cuesta, and G. G. de la Iglesia, "Real-time Win Prediction in League of Legends," in Proc. 2019 IEEE 7th Int. Conf. on Serious Games and Applications for Health (SeGAH), 2019, pp. 1-7.
[4] J. P. Hsieh, Z. C. Lee, and P. Y. Chen, "Network analysis of composition strategies in Teamfight Tactics," arXiv preprint arXiv:1909.07446, 2019.
[5] D. W. Hosmer Jr., S. Lemeshow, and R. X. Sturdivant, Applied Logistic Regression, 3rd ed. Hoboken, NJ: John Wiley & Sons, 2013.