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Interpretable predictive framework for Mobile legends match outcome using analytic hierarchy process weighted logistic regression variants

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HIGHLIGHTS

- Hybrid framework combining analytic hierarchy process with logistic regression.
- Expert judgments yield snowball/comeback scores to quantify team state.
- Eight logistic variants capture additive, subtractive, ratio, and interaction effects.
- Evaluated on primary Mobile Legends: Bang Bang data with accuracy, F1-score, and log-loss.
- Links model structure to gameplay mechanics, improving interpretability.

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ABSTRACT

Predictive modelling in Multiplayer Online Battle Arena (MOBA) games, such as Mobile Legends: Bang Bang (MLBB), presents unique challenges due to the dynamic interplay between early advantage (*snowball*) and strategic recovery (*comeback*). Traditional machine learning models often fail to capture this temporal complexity and strategic dominance. In this study, a novel framework is proposed, integrating Analytic Hierarchy Process (AHP)-derived weights with eight variants of logistic regression (LR) models to predict match outcomes across three temporal game phases, namely early, mid, and late. In the AHP framework, expert knowledge was obtained from 20 high-ranked players where pairwise comparison matrices were screened for consistency ratio and aggregated across experts using geometric mean to obtain group priorities, formalized into two criteria as composite *snowball S* and *comeback C* scores based on eight sub-criteria. These scores were then used as structured inputs to eight LR model variants ranging from baseline and regularized models to those incorporating interaction terms, polynomial expansions, logarithmic transformations, ratio-based features, and subtractive relationships. Using an authentic primary dataset of 175 ranked MLBB match replays recorded from the experts under approved protocol, we evaluated model performance across accuracy, F1-score, and log-loss using in-game parameters extracted at 5, 12, and 20 min. We reported the performance metrics of all the model variants per-phase and by averages for comparative comparison. The calibration with reliability diagrams, Brier score, expected calibration error (ECE), and the calibration intercept-slope were evaluated, and decision curve analysis was performed. These findings suggest that modelling the balance between *snowball* and *comeback* strategies provides a mathematically sound and game-meaningful basis for improving prediction reliability. Furthermore, temporal segmentation and human-aligned feature engineering enhance model interpretability without sacrificing performance. This study advances explainable esports analytics and offers a robust modelling paradigm applicable to dynamic team-based competitive environments.

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