Research Framework & Methodology

1. Introduction Overview

This report outlines the Research Framework designed for the League of Legends Champion Recommender System. The framework follows a systematic Input-Process-Output (IPO) model, demonstrating how user psychological data is transformed into personalized champion recommendations through machine learning techniques.

2. Research Framework Diagram

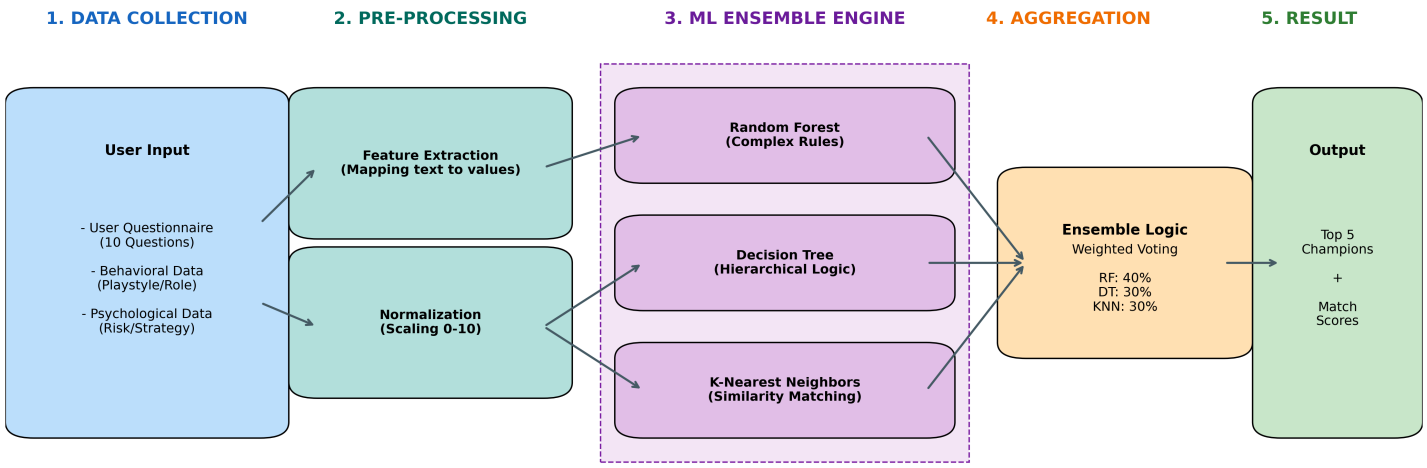

Figure 1: Input-Process-Output Model of the Recommender System

3. Framework Architecture Detail

The research framework functions as a complex three-tiered pipeline effectively translating the subtleties of human communication into actionable digital data.

A. Input Phase (Data Collection)

The Input Phase moves beyond simple statistics to build a multi-faceted 'Comprehensive User Profile'. Through a specialized questionnaire, the system captures two distinct data streams: explicit 'Behavioral Traits' (such as role preference or aggression levels) and implicit 'Psychological Traits' (measuring abstract qualities like risk tolerance and strategic foresight). These dimensions are synthesized into a holistic input, ensuring the model aligns the player's personality with their mechanical preferences.

B. Process Phase (The Analytical Engine)

The Process Phase serves as the system's core intelligence. Instead of relying on a single algorithm, the

framework employs an 'Ensemble Machine Learning Architecture' acting as a computational 'Panel of Experts'. This engine harnesses the collective power of three models: a Random Forest classifier to identify complex, non-linear interactions; a Decision Tree for transparent, rule-based logic; and K-Nearest Neighbors (KNN) for mathematical similarity matching. This ensemble approach mitigates individual algorithmic bias and significantly enhances prediction accuracy.

C. Output Phase (Actionable Intelligence)

The Output Phase converts raw probabilities into 'Actionable Intelligence'. To guarantee relevance and variety, specific metrics such as Precision@K and Diversity are applied to filter and rank the results, producing a tailored list of 'Champion Recommendations'. Fundamentally, the framework is designed to facilitate a cyclical feedback loop; user interactions and ratings serve as recursive inputs, allowing the system to iteratively refine its understanding and improve performance over time.