Research on Dark Personality Prediction Techniques Based on Gaming Behavior

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Abstract

[目的]This study utilizes DOTA2 gameplay behavior data to achieve non-intrusive identification of the three dimensions of dark personality in DOTA2 players.

[方法]This study employs the Clarity 2 parser package to parse DOTA2 game log files, extracts players' gameplay behavior features, and utilizes the Dark Triad Dirty Dozen scale to label these features, adopting machine learning methods to identify the three dimensions of dark personality.

[结果]The results demonstrate that for the three dimensions of Machiavellianism, narcissism, and psychopathy, the model constructed using the Gaussian Process Regression algorithm exhibits optimal validity and reliability, with correlation coefficients between predicted and actual values ranging from 0.31 to 0.45, and test-retest reliability coefficients ranging from 0.33 to 0.53.

[局限]This study did not incorporate subjects' verbal behavior features into the modeling process, resulting in gameplay behavior features that are not sufficiently comprehensive.

[结论]The study findings indicate that gameplay behavior data can facilitate prediction of individuals' dark personality, and models constructed via Gaussian Process Regression demonstrate the highest reliability and validity.

Full Text

Preamble

Research on Dark Personality Prediction Technology Based on Game Behavior Sihua Lyu[12], Wenwen Chen[3], Yichuan Zhang[3], Tingshao Zhu[12*]

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Abstract:
[Objective] This study utilizes DOTA2 gameplay behavioral data to achieve non-intrusive identification of the three dimensions of Dark Personality among DOTA2 players.
[Methods] We employed the Clarity 2 parsing package to parse DOTA2 game log files, extracted players' gameplay behavioral features, and used the Dirty Dozen scale to label these features. Machine learning methods were then adopted to identify the three dimensions of Dark Personality.
[Results] Results demonstrated that models built using Gaussian Process Regression achieved the best performance in terms of validity and reliability across Machiavellianism, narcissism, and psychopathy dimensions. The correlation coefficients between predicted and actual values ranged from 0.31 to 0.45, with test-retest reliability coefficients between 0.33 and 0.53.
[Limitations] This study did not incorporate players' verbal behavioral features into the modeling process, resulting in incomplete gameplay behavioral features.
[Conclusions] The findings indicate that gameplay behavioral data can help predict individuals' Dark Personality, and models built through Gaussian Process Regression exhibit the highest validity and reliability.

Keywords: Dark Personality, gameplay behavior, machine learning, DOTA2
Classification Number: B849

Dark Personality Prediction from Player in-game Behavior: Machine Learning Methods

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Abstract:
[Objective] By utilizing players' behavioral data in DOTA2, this study proposes a non-intrusive method to identify the Dark Personality of game players.
[Methods] After extracting behavioral features from DOTA2 replay files with the help of the parsing tool Clarity 2 package, and obtaining players' dark personality through the Dirty Dozen scale, we employed machine learning methods to predict players' sub-dimensions of Dark Personality.
[Results] Results showed that the best performance occurred with Gaussian Process Regression on Machiavellianism, narcissism, and psychopathy. The correlations between predicted values and actual values were between 0.31 and 0.45, and the test-retest correlations were between 0.33 and 0.53.
[Limitations] This study did not involve players' verbal behavior in the process of establishing models, resulting in feature sets that were not comprehensive enough.

[Conclusions] It is suggested that in-game behavior data is able to help predict the Dark Personality of players, and the models built by Gaussian Process Regression had the best results in terms of validity and reliability.

Key words: Dark Personality; in-game behavior; machine learning; DOTA2

Dark Personality, as one of the most representative personality trait clusters [1], reflects the "dark side" of human nature through three dimensions: Machiavellianism, narcissism, and psychopathy [2]. Previous studies have demonstrated that individuals' Dark Personality is associated with their gaming strategies and genre preferences. Malesza [3], based on research using the Prisoner' s Dilemma game, proposed that levels of Machiavellianism and psychopathy are significantly positively correlated with the frequency of defection behaviors in games. Curtis et al. [4], using the "Flipit" game as a research tool, found that Machiavellianism is related to players' strategic orientation, psychopathy is associated with direct aggressive behavior, and narcissism is linked to overconfident behavior. In research on game genre preferences, Melzer [5] noted that players with high levels of psychopathy and Machiavellianism prefer violent and antisocial-themed games. These findings indicate that individuals' Dark Personality can influence their gaming strategies and choices. If we can predict individuals' Dark Personality, we can further help gaming companies optimize their internal player matching algorithms and game recommendation mechanisms, thereby enhancing the gaming combat experience and the accuracy of recommendation algorithms.

Currently, the most widely used method for personality measurement is the questionnaire method, which offers operational convenience and relatively high validity and reliability [6]. However, this approach also has several limitations. First, questionnaires require participants' willingness to self-report, making them difficult to administer when participants are relatively uncooperative [7]. Second, the questionnaire format can be tedious; if the number of items is large, participants may experience fatigue, leading to negative emotions and further reducing their willingness to complete the survey. If game operators expect to obtain Dark Personality traits from large numbers of players, implementing this through questionnaires makes it difficult to ensure that all users are willing to cooperate and that the process does not create a negative gaming experience. An alternative approach is game-based assessment, which refers to the identification and quantification of individual psychological characteristics based on games or gamified activities [8]. The scope of "games" here is broad, encompassing real-world competitive scenarios such as mahjong and card games, as well as virtual online environments like MOBA games. This type of assessment offers two advantages: first, its diverse and interesting test formats and scenarios can enhance respondents' motivation and engagement [9]; second, it is ecological and non-intrusive, requiring only user authorization to access their data without relying on self-reporting, thus causing no disturbance to participants [7]. Therefore, adopting game-based assessment can overcome some of the limitations of questionnaire measurements in applied scenarios. In fact, scholars have already attempted to use different forms of games for personality assessment [10], and these studies demonstrate that predicting individual personality from game behavior is feasible.

To predict Dark Personality based on game behavior, the selection of games and the ability to comprehensively obtain gameplay behavior become particularly critical. Among all current online game categories, Multiplayer Online Battle Arena (MOBA) games possess high scenario complexity. By simulating complex competitive environments, they can more realistically reproduce human behavior in such settings. Compared to First-Person Shooting (FPS) games and battle royale games (a third-person shooting game mode), MOBA games place greater emphasis on players' strategic and tactical decision-making. Additionally, although MOBA games emerged relatively recently, according to the "Global Esports Industry Development Report" released by Penguin Intelligence [14], MOBA games have become one of the most popular esports genres, with the most prominent titles including "League of Legends" and "DOTA2." Furthermore, with the development of MOBA games, some titles such as DOTA2 can record each match' s behavioral data through log files and have spawned their own parsing tools. The "Clarity 2" package available on GitHub (https://github.com/odota/clarity) can be used to parse these game log files. Moreover, DOTA2 has its own open data platform, OpenDota (https://www.opendota.com/), where searching for a player' s Steam ID yields their historical game data. Based on these considerations—DOTA2 being a MOBA game with mature parsing tools and a game data platform—this study aims to predict players' Dark Personality through DOTA2 gameplay behavior. While the DOTA2 gameplay behaviors obtained through parsing tools are numerous and complex, the era of big data has made machine learning an important means for discovering data patterns. Researchers have already begun attempting to use machine learning tools for predicting the Big Five personality traits.

Yee [12] employed multiple regression analysis, using behavioral features from "World of Warcraft"that showed high correlations with each dimension to predict Big Five personality dimensions. All dimensions could be significantly predicted, with correlation coefficients between predicted and actual values ranging from 0.2 to 0.3. Bunian et al. [13] used Hidden Markov Models to extract behavioral sequence features and logistic regression to classify players' Big Five personality scores as high or low, achieving classification accuracy between 54% and 60%. Therefore, this study will also leverage machine learning tools to attempt to discover patterns hidden between DOTA2 gameplay behavior and risk tendencies.

In summary, to compensate for the limitations of questionnaire methods in measuring Dark Personality in applied scenarios, this study proposes to predict the three dimensions of Dark Personality based on DOTA2 gameplay behavioral data using machine learning methods.

2.1 Participants

Using snowball sampling, game forum postings, and other methods, we recruited 296 valid participants, including 286 males (96.6% of the total) with a mean age of 22.97 years (SD = 2.29). All participants had at least a high school education. The screening criteria for valid samples included three points: 1) Game duration greater than 10 hours. To avoid situations where participants' unfamiliarity with the game environment and rules prevented their behavior from effectively reflecting their personality traits, the screening threshold required actual online gameplay time to exceed 10 hours. 2) Questionnaire completion time greater than 300 seconds. If questionnaire completion time was too short, the validity of the results was questionable, and such cases were removed. 3) Attention check questions. The questionnaire included attention check items, such as "Please select 2020 for this question." Incorrect answers indicated low participant focus and questionable validity, leading to removal. To test model reliability, valid samples from 59 participants were designated as the retest sample set during regression model construction.

2.2 Research Tools

(1) **Questionnaires**
Basic Player Information Questionnaire. This section collected basic demographic information, including gender, age, residence, marital status, education, monthly income, and Steam ID.

Dirty Dozen (DD) Scale. This scale consists of 12 items across three dimensions: Machiavellianism, narcissism, and psychopathy [15]. Using a seven-point rating scale, total scores and factor scores were calculated, with higher scores indicating higher levels of a particular dimension.

(2) **DOTA2**
This study used DOTA2 version 7.29. DOTA2 is a multiplayer competitive game requiring two teams of five players to initiate each match. Typically, opponents and teammates are assembled through system matching or room creation invitations. The skill level of opponents and teammates influences players' combat strategies and behaviors. For example, when encountering exceptionally skilled teammates, a player who normally specializes in the carry position might choose a support role instead. When facing overly strong opponents, a player who prefers aggressive strategies might switch to non-direct confrontation tactics. Therefore, to better reproduce players'psychological characteristics, this study controlled for map variables and opponent/teammate skill levels by unifying game room settings to ensure consistent game maps, opponents, and teammates across participants (see Figure 1 [Figure 1: see original paper]).

1) **Map Variables**. The game map determines the positions of both factions and resource point distribution. In actual gameplay, factors such as faction distance, tower-pushing routes, and resource point density and

placement all affect player behavior and operations. Therefore, this experiment unified map variables and fixed all participants in the lower-left corner of the map, using this point as the origin for all gameplay.

2) **Opponent and Teammate Skill Levels**. The skill level of opponents and teammates affects participants' combat strategies and behaviors. Therefore, this experiment unified game difficulty and mode, setting difficulty to "Hard" and mode to "Bot Match," meaning that in experimental matches, participants' opponents and teammates were AI bots with similar combat levels, with AI player rosters randomly matched by the system.

Figure 1 Screenshot of game room settings under experimental conditions

2.3 Data Collection

Data collection consisted of two parts: single-match log file collection and historical game data crawling. The experimental procedure for single-match log file collection was as follows: 1) The experimenter added participants' contact information, explained the experimental purpose, and obtained consent. Before the experiment, participants were instructed to install DOTA2 version 7.29 and log into their personal accounts in advance. 2) The experimenter guided participants to complete the basic demographic questionnaire and Dark Personality scale online, ensuring completion and submission. 3) Through screen sharing, the experimenter confirmed that participants' game room settings matched experimental conditions—specifically, setting game mode to "All Heroes" and "Bot Match," with difficulty set to "Hard." 4) After the game, participants saved the game log file and submitted it to the experimenter under guidance. 5) After verifying that both log files and questionnaire data were collected correctly, the experimenter issued compensation.

Historical game data crawling was conducted uniformly after all single-match log file collection was completed. Using a Python crawler and participants' Steam IDs from the basic information, we crawled historical game data. Due to server response failures for some players, historical data crawling failed for 24 participants, resulting in historical game data for 272 participants.

To further test model prediction reliability, we conducted repeated data collection for 59 retest participants after a one-month interval. Under identical experimental conditions, participants completed another DOTA2 match, yielding game log files, and we crawled their historical game data again. Historical data crawling failed for 2 players.

2.4 Data Processing

(1) **Feature Extraction**

This study used the Clarity2 package available on GitHub to parse game log files. Through a JAVA program, we parsed collected player game log files into data tables, extracting 198 fields in total. After removing data unrelated to gameplay behavior (such as client storage paths), 158 fields remained relevant to gameplay behavior. These covered:

- Basic match information fields: match mode, match type, player count, game duration
- Faction information fields: tower status, barracks status, scores, total team data
- Chat information fields: chat timing, speakers, tokenized chat content, and word frequencies
- Hero selection fields: banned heroes and heroes selected by each team
- Major event fields: event timing, event type, event targets
- Team fight fields: team fight start and end times, skill and item usage by each unit
- Player personal information fields: individual data such as gold, experience, skills, equipment, various kill counts

Based on these fields, we designed three major categories of features: match statistics features, player statistics features, and player operation features, further subdivided into 10 subcategories: faction information, major events, team fight information, skill usage, combat statistics, damage statistics, equipment purchase, hero selection, scouting behavior, and command proportion, totaling 114 gameplay behavioral features. Some features were borrowed from other studies and adapted; others were developed heuristically based on gaming experience and actual extracted gameplay data, then validated in subsequent modeling. The feature extraction procedure was as follows:

1) According to the game log file parsing program, files were parsed into multiple data tables stored in a MySQL data warehouse.
2) We identified three tables relevant to required features: matches, match_{logs}, and player_{matches}, exported in CSV format. The matches table stored match statistics features related to team fight information, match_{logs} stored match-related information, and player_{matches} stored all player statistics and operation features.
3) Through Python programs, data from the three tables was transformed and extracted into the required format for feature design. Based on different storage types in the tables, data extraction required different approaches:
    - For statistical features with one-to-one correspondence between raw and feature data (e.g., player kill count), raw data was directly entered into the feature table.
    - For raw data stored as dictionaries corresponding to multiple features (e.g., player commands stored as dictionaries with command types as keys and counts as values), each dictionary key was mapped to corresponding features with values entered accordingly.
    - For raw data stored as dictionaries where multiple keys corresponded

to multiple features (e.g., player kill counts by unit type stored as dictionaries with unit names as keys), values for similar unit types were integrated and entered into corresponding features.

- For raw data stored as lists of cumulative per-minute data (e.g., player gold as a list where element count equals match duration in minutes and the nth element represents total gold at minute n+1), these lists were converted from cumulative to incremental per-minute values, with the resulting lists processed as time series data to calculate mean, standard deviation, skewness, and kurtosis.
- For information stored as strings, mapping relationships were applied to convert to categorical data.
- For complex nested data (e.g., team fight information stored as lists containing dictionaries that contain lists, including each team fight' s start/end times, skill usage, target selection, damage dealt, etc.), feature extraction required identifying relevant information according to feature design rules and organizing it into the feature dataset.

4) Python programs merged each player' s feature data into a single table. The overall process is illustrated in Figure 2 [Figure 2: see original paper].

Figure 2 Feature extraction flowchart

(2) **Data Transformation**
Data Standardization. The purpose of standardization is to eliminate units of measurement, maintain data at the same scale, and reduce variance effects. Specifically, we used SPSS to convert all features to Z-scores for standardized scores.

Dummy Variable Conversion. This aims to facilitate model processing of multi-categorical variables and ensure readable results. Fields requiring dummy variable conversion include hero type, recommended classification, actual lane position, and maximum damage period fields.

(3) **Feature Selection**
Based on the normalized original feature set, we used the Wrapper method for feature screening. The Wrapper method embeds the machine learning algorithm to be used in subsequent modeling into the feature selection process, determining feature subset quality by testing prediction performance on the modeling algorithm. This method does not require optimal performance from each individual feature in the subset, only ensuring that the selected subset is optimal for the subsequent modeling algorithm [16].

3.1 Personality-Behavior Correlation Analysis

Based on scale information from 296 valid samples, the means and standard deviations of Dark Personality sub-dimensions are shown in Table 1 . We conducted normality tests on personality questionnaire scores and behavioral indicators from 296 valid participants using histograms, P-P plots, and Q-Q plots. Pearson correlation coefficients were calculated for normally distributed variables, while Spearman correlations were computed for non-normal variables. The purpose was to identify indicators correlated with Dark Personality sub-dimensions to lay the foundation for subsequent modeling. Correlation test results are presented in Table 2 .

Table 1 Dark Personality Dimension Scores (M±SD)
Machiavellianism

Table 2 Summary of Correlation Coefficients Between Dark Personality Scale Scores and Player Behavioral Indicators
Command Type 3 Proportion
Command Type 8 Proportion
Command Type 21 Proportion
Command Type 31 Proportion
Player Death Count
Player Experience Kurtosis
Player Experience Skewness
Player Tower Damage Taken Proportion
Consumable Purchase Quantity
Total Observer Wards Placed
Mean Observer Wards Placed
Standard Deviation of Observer Wards Placed
Skewness of Observer Wards Placed

Note: *p<0.05, **p<0.01

Machiavellianism showed significant positive correlations with player tower damage taken proportion ($r = 0.19$, $p < 0.01$), command type 8 proportion ($r = 0.14$, $p < 0.05$), and command type 21 proportion ($r = 0.14$, $p < 0.05$). Psychopathy showed significant negative correlations with command type 31 proportion ($r = -0.14$, $p < 0.05$) and consumable purchase quantity ($r = -0.13$, $p < 0.05$). Narcissism showed significant positive correlations with player experience skewness ($r = 0.19$, $p < 0.01$) and player experience kurtosis ($r = 0.15$, $p < 0.05$), and significant negative correlations with command type 3 proportion ($r = -0.13$, $p < 0.05$), total observer wards placed ($r = -0.15$, $p < 0.05$), mean observer wards placed ($r = -0.15$, $p < 0.05$), standard deviation of observer wards placed ($r = -0.15$, $p < 0.05$), and skewness of observer wards placed ($r = -0.15$, $p < 0.05$).

3.2 Model Training

This study tested multiple machine learning algorithms, including Gaussian Process Regression and Support Vector Regression, embedding them into the gameplay feature selection process. We then trained models for each dimension using the corresponding machine learning methods and evaluated them using 10-fold cross-validation. Tables 3, 4, and 5 present the four best-performing algorithms. As shown, for all three dimensions—Machiavellianism, psychopathy, and narcissism—models using Gaussian Process Regression embedded in feature selection achieved the best results.

For Machiavellianism, the correlation between predicted and actual values was 0.31, with a Root Mean Squared Logarithmic Error (RMSLE) of 5.13. The model retained 13 features: early-stage total team fights, command type 1 proportion, command type 6 proportion, command type 13 proportion, command type 21 proportion, player tower damage taken proportion, whether a strength hero, active item usage count, total observer wards placed, mean observer wards placed, courier kills, kill standard deviation, and maximum damage value.

For psychopathy, the correlation between predicted and actual values was 0.36, with an RMSLE of 4.49. The model retained 16 features: mid-stage total team fights, proportion of skill usage on allies, command type 12 proportion, command type 27 proportion, command type 29 proportion, command type 31 proportion, player deny count, total gold, total stun duration, mean player deny count, player tower damage taken proportion, attack equipment purchase quantity, defense equipment purchase quantity, consumable purchase quantity, neutral creep kills, and maximum damage value.

For narcissism, the correlation between predicted and actual values was 0.45, with an RMSLE of 4.52. The model retained 22 features: total team fights, proportion of skill usage on self, command type 3 proportion, command type 9 proportion, command type 18 proportion, command type 19 proportion, command type 21 proportion, command type 37 proportion, player kill count, player gold standard deviation, player gold kurtosis, player experience skewness, buyback count, player damage proportion of team total, player damage proportion to heroes, player damage proportion to neutral creeps, player tower damage taken proportion, active item usage count, consumable purchase quantity, total observer wards placed, skewness of sentry wards placed, and mean observer wards placed.

Table 3 Machiavellianism Regression Prediction Model Results
Dimension | Screening Method
KStar | Wrapper

Dimension | Screening Method

Table 4 Psychopathy Regression Prediction Model Results
KStar | Wrapper

Table 5 Narcissism Regression Prediction Model Results
Dimension | Screening Method
Wrapper | KStar

3.2 Test-Retest Reliability

Considering that the model with the best validity might not necessarily show the best test-retest reliability, this study conducted test-retest reliability tests on all prediction models built with different algorithms for each dimension to select models with optimal validity and reliability. Based on retest participants' data from both gaming sessions, we identified the gameplay behavioral features required for prediction by each model. The first (initial test) and second (retest) gameplay behavioral features were input separately to obtain initial and retest predicted values, and their Pearson correlation coefficient was calculated as the model' s test-retest reliability.

The final correlations between predicted and actual scores for the three Dark Personality dimensions are summarized in Table 6 .

Table 6 Summary of Test-Retest Reliability for Dark Personality Dimensions
KStar
Machiavellianism: 0.53** | 0.38** | 0.33*
Note: *p<0.05, **p<0.01

Psychopathy: 0.39** | 0.56** | 0.45** | 0.29* | 0.37** | 0.29* | 0.38**

As shown, for Machiavellianism, psychopathy, and narcissism, models built using Gaussian Process Regression (GPR) achieved both the highest validity and the most robust reliability, with test-retest reliability coefficients of 0.53, 0.38, and 0.33, respectively.

This study first employed correlational statistical analysis to describe the fundamental associations between DOTA2 gameplay behavior and Dark Personality traits, and then used machine learning methods to achieve non-intrusive prediction of Machiavellianism, psychopathy, and narcissism dimensions.

Regarding the correlation findings, for Machiavellianism, tower damage taken proportion showed a positive correlation. According to Qin and Xu [2], individuals scoring high on Machiavellianism are more ruthless and results-oriented. Towers are defensive structures that protect the base and allied players, attacking enemies when they enter its range and damage allied players. Tower damage taken proportion represents the ratio of damage dealt to a player by towers relative to their total damage taken during a match. A higher proportion indicates more frequent attacks on opponents under towers, willing to endure tower damage to secure kills. This proportion can thus reflect players' ruthless and results-oriented traits to some extent.

In terms of model training, all three dimensions achieved the best validity and reliability when using Gaussian Process Regression, demonstrating that GPR is relatively suitable for the gameplay behavioral data in this study. The correlation coefficients between predicted and actual values ranged from 0.31 to 0.45, RMSLE values ranged from 4.49 to 5.13, and test-retest reliability coefficients ranged from 0.33 to 0.53, indicating that the regression prediction models possess certain validity and reliability with practical application value. This study has limitations: since participants played in human vs. AI mode, where all combat positions except the player were bots, there was no verbal behavior during gameplay. This differs from real-life scenarios where players typically communicate with teammates via voice or text while playing. The experimental environment control thus resulted in missing verbal behavioral features, and future research should incorporate players' verbal behavior into model development.

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Author Contributions Statement

Tingshao Zhu, Yichuan Zhang, Wenwen Chen: Proposed research ideas and designed research protocol
Yichuan Zhang, Wenwen Chen, Sihua Lyu: Implemented research procedures, such as conducting experiments or surveys

Sihua Lyu: Historical data crawling
Tingshao Zhu: Gameplay behavioral data acquisition and overall design
Yichuan Zhang, Wenwen Chen: Data analysis
Sihua Lyu, Wenwen Chen, Yichuan Zhang, Tingshao Zhu: Drafted or revised the final manuscript

Note: Figure translations are in progress. See original paper for figures.