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What Contributes to Success in MOBA Games? An Empirical Study of Defense of the Ancients 2

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Abstract

With the development of computer science and Internet technology, online games have become one of the most important sources of entertainment in daily life. Meanwhile, increasing attention has been paid to top international electronic sports (eSports) tournaments in which competitive pressure is becoming increasingly more serious. Therefore, how to win such games is a problem worth exploring. This article proposes a set of evaluation indicators for testing gameplay in Defense of the Ancients 2, which is a popular multiplayer online game. The analysis shows that the multiplayer killing indicator is an effective predictor of the game result. Furthermore, the evaluation indicators are divided into two categories: operational skills and tactical awareness. The functions of the indicators in each category are discussed. The results show that, for professional eSports teams, tactical awareness affects the multiplayer killing indicator and the game result more so than operational skills.

Keywords

effective predictor, Dota 2, tactical awareness, operational skills, multiplayer

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Introduction

With the development of computer science and Internet technology, online games have become one of the most important sources of entertainment in daily life. In America, 72% of households play video games (Entertainment Software Association, 2011). The gaming industry has evolved from the simple formula of making money by selling software into a new industry characterized by combining patterns and experience in the fields of sports and cultural creativity; this is a key developing industry in America and other developed European countries. China has supported the electronic sports (eSports) industry since 2003, when the State General Administration of Sports added eSports to the state sports program. eSports have been nominated for the 2020 Olympic Games and may represent an up-and-coming profession. Thus, the gaming industry plays a significant role in network societies.

One popular genre of video games, multiplayer online battle arena (MOBA) games, is a common choice for many eSports tournaments. MOBAs are a hybrid of the massively multiplayer online game and real-time strategy (RTS) genres. Such games center around two small teams competing against one another (Kahn & Williams, 2016). Recent years have witnessed the explosion of MOBA-related studies from various perspectives such as game addiction, motivation, leadership, and cultural differences. Our study explores the winning predictors in Defense of the Ancients 2 (Dota 2), which is a popular MOBA game. The objective of this study is to determine how to achieve victory as well as extract good team cooperation patterns and strategies, which are important to the MOBA genre for the sake of better competition. Due to the sports-based nature of eSports gameplay, this study represents an effective way of distinguishing and optimizing talent in terms of both out-of-game and in-game factors while also providing valuable references for future game design.

Factors That Affect Game Results

At present, research into factors that affect game results can be divided into two main categories: out-of-game factors and in-game factors. Out-of-games factors mainly involve differences in demographic features, such as gender and cultural differences, whereas in-game factors mainly consist of mechanics and tactical awareness. These factors together affect final success in a specific game. According to McGrath's (1984) circumplex model of group tasks, MOBA games belong to a specific type of group task called contest/battle tasks, of which success has to be considered based on two distinct metrics: performance and outcome. A strong performance does not guarantee a win, and a weak performance does not guarantee a loss (Kahn & Williams, 2016). Thus, it is necessary to note that success as it is referred to in the present article is operationalized as outcome.

Concerning out-of-game factors, a number of studies have examined the effects of gender and culture on game results. Gender differences can lead to different game behaviors, thus resulting in different outcomes. Numerous studies have shown that female participants are more likely to start off as healers or as party support due to a lack of confidence (Carr & Oliver, 2009; Nardi, 2010; Ratan, Kennedy, & Williams, 2012; Ratan, Taylor, Hogan, Kennedy, & Williams, 2015; Williams et al., 2006). In contrast to gender studies in video games, cultural studies focus on the differences between East Asian countries and Western cultures. Cultural differences usually lead to distinctions in game design between East Asian countries and Western countries. For instance, video games in East Asian countries tend to be simplistic, varied, and moderate, whereas video games in Western countries tend to be sophisticated and competitive and apply more advanced techniques (Chen, 2014; Lai, 2003). These gender and cultural differences result in group divisions when choosing game types, thus contributing to different game results.

Many articles on in-game factors state that personal skill level is crucial due to its important influence on completing game missions and achieving final success. Operational capability is the critical component of personal skills and includes clever movement, rapid response, good hand-eye coordination (Ranbusch, Jakobsson, & Pargman, 2007; Reeves, Brown, & Laurier, 2009). It has also been shown that well-skilled players can exhibit stable performance regardless of whether the game server is good (Armitage, 2003; Henderson, 2001). A recent study on non-verbal communication and team performance in League of Legends operationalized performance with four constructs: the kills, deaths, assists, and gold of each player (Leavitt, Keegan, & Clark, 2016). These four constructs also reflect personal skill level.

Conversely, other studies have emphasized the importance of team work and compromise. The game rules that are displayed on the official website are not entirely comprehensive (Neuenschwander, 2008). Teams and organizations provide more comprehensive information and resources to game players while satisfying their social needs in a game (Chen, 2010; Kou & Gui, 2014; van de Bovenkamp, Shen, Iosup, & Kuipers, 2013). In addition, some studies have noted that friendship is crucial in team cooperation, which promotes both individual and team performance and avoids the risks associated with having to cooperate with strangers (Bardzell, Bardzell, Pace, & Reed, 2008; Mason & Clauset, 2013; Xu, Cao, Sellen, Herbrich, & Graepel, 2011).

As demonstrated by a number of studies on video games, team cooperation is a primary motivation for game players (Lindtner et al., 2008; Nardi & Harris, 2006; Yee, 2006) and has a positive effect on social capital and civic participation in online games (Zhong, 2011). Game players cooperate in different organizational forms, the most common of which is a guild. Relevant studies have explored the demographics, personal identity, organizational structures, and life cycles of guilds (Ducheneaut, Yee, Nickell, & Moore, 2007; Pisan, 2007). Team cooperation is important in online games, especially large games with millions of participants. Organizations, such as guilds and families, provide members with enormous assistance and protection and help to design the growth path of their members (Bardzell, Nichols, Pace, & Bardzell, 2012).

Discussing in-game factors such as mechanics and team cooperation, Donaldson (2015) integrated the various dividing methods of game factors and proposed a binary model of expertise for League of Legends, therein outlining examples of the in-game and out-of-game practices used by players in their pursuit of competitive success. He argued that metagame expertise is more important than mechanic expertise. Mechanic expertise involves personal operational control, including selecting the camera position and controlling the champion, whereas metagame expertise involves analyzing current game conditions, building new strategies, and redistributing tasks. The central elements of the metagame are team cooperation and good tactical awareness. In Donaldson's opinion, if a game player lacks metagame expertise, he will be at a disadvantage in the game even if he has good operational control ability.

Furthermore, based on the similarities between eSports and sports, it is necessary to explore the strategies and methodologies adopted in the study of sports. As popular international sports, football and basketball have received the greatest amounts of academic attention, and studies refer to many aspects such as the physical quality of players, the hiring decisions made by agents, and the prediction of sports outcomes (Fry, Lundberg, & Ohlmann, 2007; McMaster, Gill, Cronin, & McGuigan, 2013). Data analysis methodologies in these studies are mainly classical statistical models, machine learning methods, or their combination (Lock & Nettleton, 2014; Young & William, 2010) such as logistic regression, random forest, decision trees, and artificial neural networks. Factors considered in sports include venue, fatigue, morale, and other aspects that have a close association with the physical status of the players (Min, Kim, Choe, Eom, & McKay, 2008) as well as operational skills and team coordination, which belong to game strategies. Because the present study mainly concentrates on the exploration of in-game strategies, factors such as venue, fatigue, and other human factors are not considered. Additionally, certain methodologies, such as logistic regression and decision trees, can also be applied to eSports analysis. As background, Dota 2 and the International Dota 2 Championships (TI) are briefly introduced to lay the foundation for the study.

Dota 2

Dota 2 is a 5v5 RTS game in which participants position and maneuver units and structures under their control to secure areas of a map and destroy the opponents' assets. It was named the best strategy game and best multiplayer game of the year by Imagine Games Network (2013), an authoritative media company on game reviews. In 2014, there were approximately 101 Dota 2 competitions, with the cumulative prize money reaching 15 million dollars, therein breaking the bonus pot record of all eSports competitions (e-Sports Earnings, 2014).

To upgrade levels and equipment, five team members must cooperate with each other and restrict competitors. Each player controls one avatar-character selected from a roster of 109 (at the time of writing) predefined heroes. As the game title indicates, the goal is to defend the ancients on one side and destroy the ancients on the enemy side. To reach the ancients on the enemy side, the heroes of one side must defeat the troops, heroes, and defensive structures of the enemies. Games have no time limit, but the matches used in the current work average approximately 40 min in length.

As one of the world's most popular video games, Dota 2 is now receiving a level of academic attention appropriate for its significance in both the eSports industry and contemporary game culture. Existing works have focused on relationships between character choices and players' leadership characteristics (Nuangjumnonga & Mitomo, 2012), the matchmaking features of two Dota communities (van de Bovenkamp et al., 2013), and cultural differences affecting team performance (Wang, Xia, & Chen, 2015). Dota 2 contains a series of indicators that predict the game results such as controlling the visual field and killing enemy heroes. Therefore, an exploration of the effective predictor in a Dota 2 match not only benefits the game players but also provides information that will be useful for organizational management. All the above are significant aspects of not only Dota 2 and the player culture but also the MOBA genre and competitive online gaming in general.

The International Dota 2 Championships

The International Dota 2 Championships (TI) were started by Valve Corporation in 2011. TI is an official international eSports competition that is famous for having the highest prize amounts among all eSports competitions. At the recent TI5, the total prize money reached approximately 18 million dollars, making it the tournament with the world's highest payout. The first prize of 6.63 million also exceeded the previous record from the Guinness Book of World Records (Guinness World Records, 2015). TI has been regarded as the global eSports competition with the most contestants and the largest prizes, thus influencing the global development of the eSports industry.

Objective of the Present Study

Previous studies have analyzed online games from different perspectives and have observed many useful aspects that lead to game victory in MOBAs such as team composition (Pobiedina, Neidhardt, Moreno, Grad-Gyenge, & Werthner, 2013), team strategies (Batsford, 2014; Guo, Shen, Visser, & Iosup, 2012; Yang, Harrison, & Roberts, 2014), and the characteristics of team players (Johnson, Nacke, & Wyeth, 2015; Kahn et al., 2015). Several quantitative studies of video games have obtained data via surveys that cannot adequately reflect behavioral information and process details. Instead of using survey data, the data in our study are obtained directly from records of game replays, which may provide a new perspective for discussing player behaviors and game elements. Previous studies have drawn the common conclusion that team cooperation is particularly important for eventual success in a game. This important viewpoint paves the way for us to further elucidate the critical indicators that predict outcomes of Dota 2, for which relevant research is lacking.

This article presents relevant studies regarding the critical indicators that predict outcomes of Dota 2, including three major aspects. First, we propose a set of evaluation indicators used to measure team performance in one specific match. Not only information on the results board but also game behaviors are taken into account to construct the evaluation indicators. Based on the evaluation indicators, observational data are obtained from the game replays of TI4 (The International Dota 2 Championships), which is a top global eSports tournament. Second, through a statistical model, the effective predictor which has the most significant relationship with outcomes of DotA2 is investigated. Finally, we distinguish the critical indicators and provide an integrated discussion on the importance of tactical awareness in Dota 2. The study attempts to answer the following research questions:

> **Research Question 1:** How does one construct the evaluation indicators based on not only the results board of DotA2 but also the players' game behaviors such as detecting the environment, assisting the teammates, and initiating an attack?
>
> **Research Question 2:** What is the effective predictor of the outcome of a specific game among all the evaluation indicators?
>
> **Research Question 3:** Among the remaining indicators, which indicators are closely connected to the effective predictor, and what characteristics do these indicators have in common?

Method and Data

Evaluation Indicators

The evaluation indicators of the present study are proposed based on the players' game behaviors. In a normal match, dozens of battles occur between the heroes of the two opposing sides. The polarization of gold and experience from these battles breaks the original balance of the two sides and becomes increasingly unbalanced until one side is sufficiently strong to defeat the other side. Therefore, we propose a set of evaluation indicators that can both reflect the conditions during these battles and be used to examine the development of the two sides' outside of fighting. Based on the source of the attack, a hero's death can be caused by either one enemy hero or two or more enemy heroes. Moreover, the indicators closely related to a battle also include the frequency of initiating fights and using smoke of deceit, which is used for ambushes. Upon activation, the hero and nearby allies become invisible in the world and on the minimap and also gain additional movement speed. This effect is dispelled when close to enemy heroes or towers. Thus, using smoke of deceit can produce a sudden hit to the enemy and must be considered as an important indicator in the battles.

In addition to fighting, environmental monitoring and killing the creeps are two critical indicators. There are two basic items for detecting the surroundings in Dota 2: the observer ward and the sentry ward. The former item is used to provide vision nearby, and the latter item is used to detect invisible enemy elements, including wards and heroes. Effective monitoring of the changing environment relies on the effective use of these two ward types. Moreover, every even-numbered minute of game time, starting at the first creep spawn, a rune spawns at one of the 2 rune-spawning locations if a rune is not already at one of the spawning locations. Each spawning location is in the river: One is northwest of the middle of the map, and the other is to the southeast. Upon activation, the runes can provide the hero with additional experience and enhance one of the hero's abilities depending on the type of rune. Therefore, activating the runes is another important indicator for controlling the environment. The lane phase includes the two game terms "last hit" and "deny." A last hit is the killing blow on an enemy creep; a player receives gold for landing the last hit on an enemy creep. Denying is achieving the last hit on your own team's creep to reduce the amount of experience given to the enemy team by 50% and to deny the enemy team gold. Therefore, the lane phase is also a key indicator influencing the game result.

In conclusion, we propose a set of evaluation indicators consisting of eleven observational variables according to common game behaviors and the relevant indicators affecting the results board of Dota 2. Table 1 shows the observation criteria of the nine quantitative variables.

These indicators include nine quantitative variables: kills by one player, kills by multiple players, initiating fights, using smoke of deceit, using observer wards, using sentry wards, activating runes, last hitting, and denying. The other two variables are qualitative variables: country and result. The evaluation indicators not only reflect the critical behavioral information in Dota 2 but also embody several cultural dimensions. Based on the theory of cultural dimensions (Hofstede, 1980, 1991; Hofstede & Hofstede, 2001; Triandis, 1995, 2001), four cultural dimensions are embodied in this set of evaluation indicators: individualism and collectivism, uncertainty avoidance, gender role, and long-term orientation. Previous research has utilized the cultural dimension characteristics of these evaluation indicators in a cross-cultural study (Wang et al., 2015).

The nine variables in Table 1 can be divided into operational skills and tactical awareness. The operating levels and control capabilities of a player are indicated by kills by one player, last hitting, and denying, which all belong to mechanics expertise. The remaining six variables embody the tactical awareness and strategic competence of a team and belong to metagame expertise. The six tactical awareness variables can be divided further. Observer wards and sentry wards are used to observe the environment and can be defined as investigation behaviors. Smoke of deceit and runes are used to create the appropriate conditions for combat and can be defined as ambush behaviors. Initiating fights and multiplayer killing are the comprehensive

Table 1. Data Observation Criteria.

Variables	Observation Criteria
Kills by one player	Observe the death of each avatar. If the source of the damage is one enemy avatar, add one point to the enemy side
Kills by multiple players	Observe the death of each avatar. If the source of the damage is more than one enemy player, add one point to the enemy side
Initiating fights	Observe each fight. If the avatars of one side launch attacks first, add one point to the corresponding team
Using smoke of deceit	When one side uses smoke of deceit, add one point to the corresponding side
Using observer wards	Count the number of times observer wards, which are solid dots on the minimap, are used
Using sentry wards	Count the number of times sentry wards, which are hollow dots on the minimap, are used
Activating runes	Observe rune-spawning locations every even-numbered minute of game time. If an avatar activates the rune, add one point to the corresponding team
Last hitting	Record the data from the results board at the end of each match
Denying	Record the data from the results board at the end of each match

Note. For each of the nine variables, the observation result is the total frequency that the corresponding behavior occurs.

responses of a team and can be defined as the warfare process. These behaviors and processes link with each other and form a complete combat chain. The degree of importance of the two sets of indicators is discussed in the following analysis.

Data Sources

The research data in this study derive from TI4. In the final of TI4, eight teams, seven of which were Chinese or American, fought for the title (Figure 1).

All the TI4 game replays can be downloaded for free on the Steam platform. One critical advantage of game replays is the reappearance of nearly all the process information and details, except for the voice chat. From Steam, we downloaded all 37 game replays between the Chinese and American teams, from which the relevant indicators were observed and recorded. Among the 16 participating teams, over half were Chinese or American. Moreover, the top five teams were all from China or America and received approximately 82.5% of all prize money from TI4. Thus, the game replays between the Chinese and American teams not only accurately represent the gameplay of TI4 but also reflect the play of world-class Dota 2 competitors. Therefore, our analysis is based on these replays.

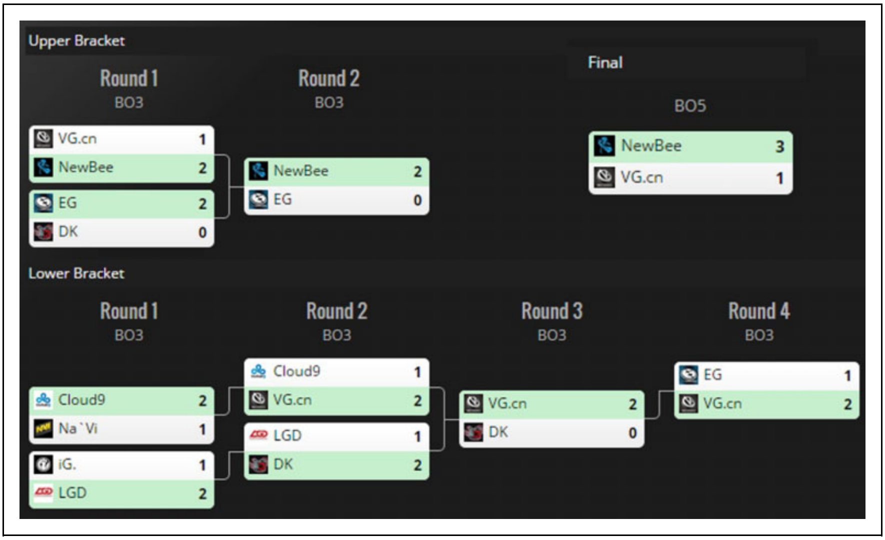

Figure 1. Playoffs of TI4 (GosuGamers, 2014).

Data Encoding Process and Results

Because of the simple structure of the data encoded, an independent encoding method was adopted to improve efficiency without decreasing reliability. We invited seven people to observe game replays and record data. All were skilled male game players whose ages ranged from 18 to 23. In particular, the observers we chose had significant Dota 2 game experience or experience with other similar games such as Dota or League of Legends. Thus, they were familiar with the game mechanics and operating system, limiting mistakes during observation. To guarantee the reliability of the observational data, we conducted a training session and took a series of measures both before and during the observations. Before the observations, collective training was conducted to introduce each of the observation standards in detail and resolve the questions raised by the observers. The training did not end until every observer thoroughly understood the observation criteria. During the observation process, every replay was observed by two people, and two data records were produced. The two records were compared to examine them for errors. If the data records of two people were consistent, the result was directly accepted as the final data. If the records were not consistent, a third observer further reviewed the inconsistencies and confirmed the final data. Among the 37 matches, differences in the data records only existed for two matches, which were further revised by a third observer. The revised data records were also confirmed again by the previous two observers. Thus, the accordance ratio of the original records was 94.6%. Variables such as country and game result were recorded directly from the game results board. Using this method, we obtained observational data for 37 matches at TI4 between Chinese and American teams.

Table 2. Observation Data for a Specific Match.

Variable	China	America	Winner
Kills by one player	4	6	America
Kills by multiple players	13	22	
Initiating fights	21	23	
Using smoke of deceit	4	7	
Using observer wards	13	12	
Using sentry wards	7	8	
Activating runes	12	14	
Last hitting	1,065	1,465	
Denying	57	31	

Based on the data observation criteria, 37 matches were observed and encoded into 37 data sets by the observers. To provide a clear illustration of the encoding results, one data item is displayed in Table 2.

The 37 data sets were all similarly recorded as shown in Table 2. The data for both sides were recorded for each match along with the winning side. Based on the observational data, we conducted a series of analyses to investigate the critical indicators affecting final game success.

Data Analysis Methodologies

R was used for statistical analysis (specifically, the “DescTools” package and the “rpart.plot” package) and visualization. To examine the differences in the evaluation indicators between winning and losing teams, nonparametric test methods, such as the Brown–Mood test and the Mood test, were used.

To distinguish the effective predictor of outcomes of Dota 2, the classification and regression tree (CART) method was used based on these evaluation indicators. CART was initially called a decision tree, whose automatic modeling can date back to the social science research of Morgan and Sonquist (1963) and Morgan and Messenger (1973). In the statistics field, the authoritative book on CART is *Classification and Regression Trees* by Breiman, Friedman, Stone, and Olshen (1984). As the name suggests, CART can not only conduct automatic modeling of original samples but also screen out the key variable that results in the best classification result. It is a simple yet effective classifier. CART is robust, especially for situations involving missing data or large numbers of variables. The modeling mechanism of CART determines the most influential variable, thus maximizing the purity of the two subclasses after classification. Therefore, we apply the CART method to explore the effective predictor of outcomes of Dota 2 between Chinese and American teams.

Finally, a linear regression was used to identify the indicators that are closely connected to the effective predictor.

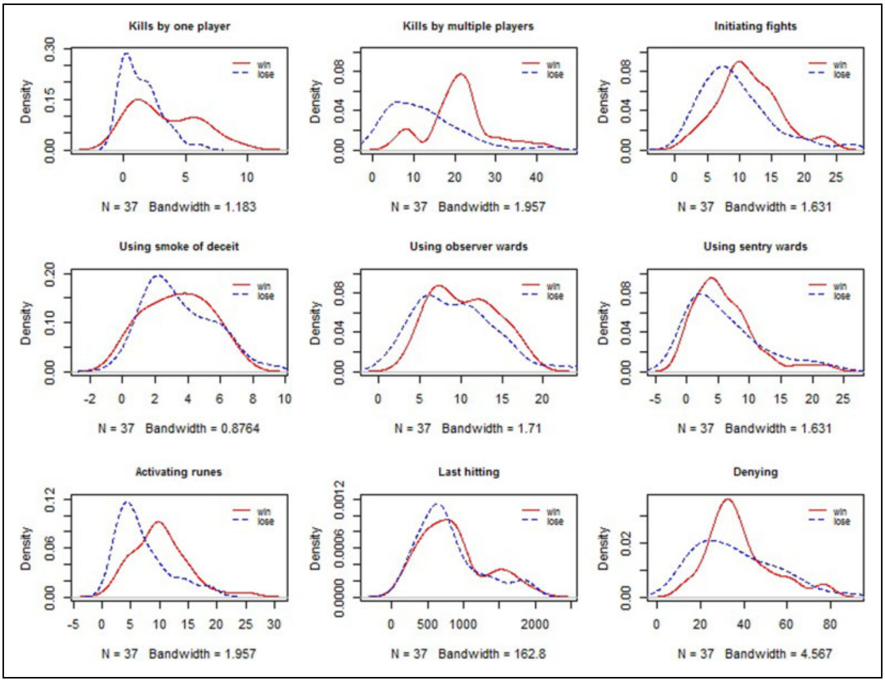

Figure 2. Density plots of each variable for winning teams and losing teams.

Results

Descriptive Findings of the Evaluation Indicators

According to common game behaviors and the relevant indicators affecting the results board of Dota 2, the evaluation indicators consist of 11 observational variables. In this section, we explore the differences between winning teams and losing teams based on the evaluation indicators in this article. This exploration aims to validate the ability of the evaluation indicators to distinguish winning sides from losing sides, which addresses issues related to Research Question 1 combined with the process of proposing the evaluation indicators. From the 37 matches, we obtained 37 data sets each from the winning teams and losing teams. Nonparametric tests were conducted to test whether significant differences existed in each of the nine variables. Figure 2 shows the density lines of the nine variables. In each subfigure, the red solid line is the probability density distribution of the winning teams, and the blue dashed line is the probability density distribution of the losing teams. Figure 2 shows that there are obvious differences between the two lines of six variables: kills by one player, kills by multiple players, initiating fights, using observer wards, activating runes, and denying. For these six variables, the red solid line is to the right of the blue dashed line in the subfigures.

Table 3. Nonparametric Test Results for Winning Teams and Losing Teams.

Variable	Brown–Mood	Mood
Kills by one player	**19 (.004)**	1.228 (.219)
Kills by multiple players	**28 (.000)**	−1.001 (.317)
Initiating fights	**23 (.004)**	−0.709 (.478)
Using smoke of deceit	18 (.371)	0.212 (.832)
Using observer wards	18 (.536)	−1.294 (.196)
Using sentry wards	16 (.707)	−1.387 (.165)
Activating runes	**26 (.000)**	−0.914 (.361)
Last hitting	21 (.163)	0.275 (.783)
Denying	19 (.642)	−1.928 (.054)

Note. The Brown–Mood method is used to verify whether the medians of the paired data are consistent. The Mood method is used to verify whether the scales of the paired data are consistent. Significant results are in bold.

Then, we used two nonparametric test methods, the Brown–Mood test and the Mood test, to verify the significant differences between the two lines in each subfigure. The Brown–Mood test was used to verify whether the medians of the paired data were the same, whereas the Mood test verified whether the scales of the paired data were the same. Table 3 provides the test results of each variable.

The test results in Table 3 show that the frequencies of four variables—kills by one player, kills by multiple players, initiating fights, and activating runes—are significantly higher on the winning teams than on the losing teams. This result is also shown in Figure 2: The red solid line is clearly to the right of the blue dashed line in the subfigures for kills by one player, kills by multiple players, initiating fights, and activating runes. This conclusion demonstrates the importance of these four variables in Dota 2. In addition, these data indicate that the proposed evaluation indicators can be used to examine the differences between winning teams and losing teams, which is the basis of the following research.

Effective Predictor: CART Analysis

The evaluation indicators reflect team performance throughout a whole game. Although not all of these indicators significantly contribute to the victory, it is possible to examine which evaluation indicator is the effective predictor that relates to the outcomes. Therefore, to distinguish the effective predictor in Dota 2 between Chinese and Americans, the CART method was used based on these evaluation indicators. The result of each match was set as the dependent variable, and the independent variables were the nine quantitative variables of each of the two countries for the evaluation indicators. Then, a CART analysis was performed to investigate the most important indicator that predicts the game result, which answers Research Question 2.

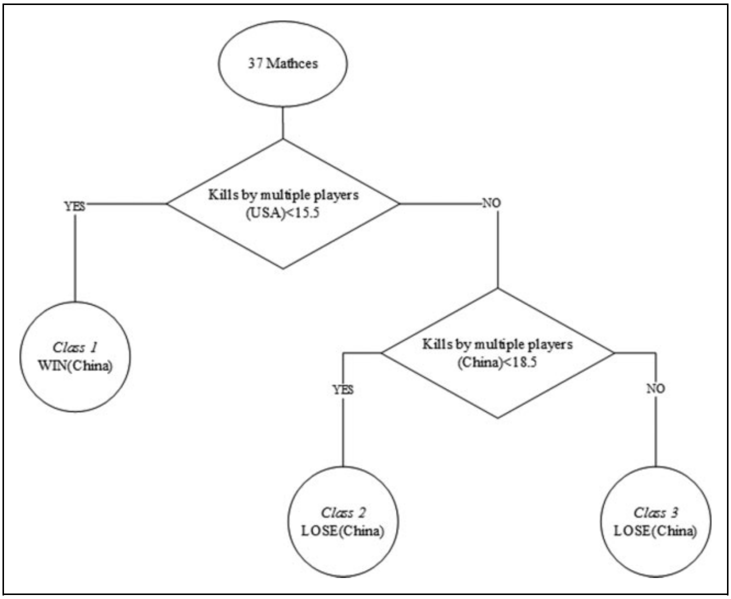

Figure 3. CART results, which show that kills by multiple players of the two opposite sides together predict game outcomes.

The CART results are shown in Figure 3. The 37 matches were divided based on the kills by multiple players of the United States into two subparts. If the Kills by multiple players of the U.S. indicator was less than 15.5, then the first class, in which the Chinese teams were the winners, was obtained. The remaining matches were divided again by the kills by multiple players of China into another subpart. One concern here is that the two subparts share the same name due to the naming convention of the CART method; a detailed explanation is given as follows. The rate of correct discrimination was 89.2%. The screened variables were the kills by multiple players of the two countries, which indicated that the result in Dota 2 depends on the kills by multiple players on both sides. In other words, kills by multiple players is the most important indicator that predicts the winning side.

Presenting the CART results as a scatterplot provides a good understanding of the classification effect (Figure 4). In Figure 4, the horizontal axis is the kills by multiple players of Chinese teams, whereas the vertical axis is the kills by multiple players of American teams. A victory by an American team is represented by a red dot, and a victory by a Chinese team is represented by a blue square. There are a total of 37 points in the figure. Based on the results of the CART analysis, two auxiliary lines (A and B) were added to the plot. A is a horizontal line along which the kills by multiple players of American teams equals 15.5, and B is a vertical line along which the kills by multiple players of Chinese teams equals 18.5. The 37 points are divided into two sections by Line A. The points below A are red dots corresponding to the

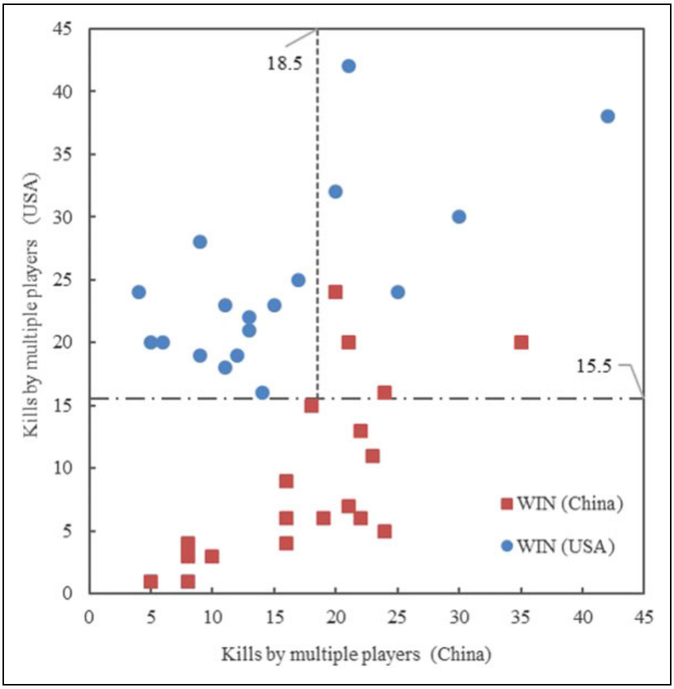

Figure 4. Scatterplot of kills by multiple players for the two countries.

first class in CART 1, whereas the points above A require further partitioning. Line B divides the part above A into two subparts. The points to the left of Line B are all blue squares corresponding to the second class of CART 1, and the subpart to the right of Line B is a hybrid block corresponding to the third class of CART 1. However, because blue squares constitute the majority of the block, at the second split of the CART analysis in Figure 3, the two branches both show “LOSE (China),” meaning that the subclass represents victories for the American teams. The naming of each branch in CART is simply based on the majority elements of the corresponding class.

To provide a clearer illustration of the relationship between the game result and the kills by multiple players of both Chinese teams and American teams, the ratio of kills by multiple players (RKM for short) between the two sides was added to the CART model as a new variable. RKM was obtained by dividing the kills by multiple players of Chinese teams by the kills by multiple players of American teams. Then, a new CART model was constructed with the game result as the dependent variable and 19 independent variables including RKM. The analysis results are illustrated in Figure 5.

Figure 5 shows that RKM is the only variable that is screened out in the new CART model; the other 18 variables were rejected. The rate of correct

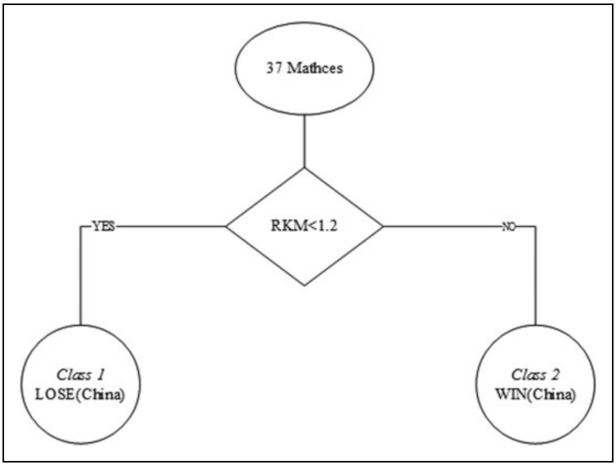

Figure 5. The classification and regression tree results, which show that ratio of kills by multiple players is the only indicator that predicts the match outcomes.

discrimination was 94.6%, representing a significant increase over the previous CART result. This improved rate of correct discrimination further clarifies that kills by multiple players is an effective predictor of outcomes of Dota 2 between Chinese teams and American teams.

Similarly, Figure 6 shows the CART results with RKM. The green dashed line is an auxiliary line along which the RKM equals 1.2. The points below the line are all red dots corresponding to the second class of CART 2, which represents victories for Chinese teams, whereas the points above the line are nearly all blue squares corresponding to the first class of CART 2, which represents victories of American teams. Only two points were classified into an incorrect class. However, there were four false distinctions in Figure 4. Specifically, adding RKM to the CART model led to a better discrimination effect. RKM illustrates that the trade-off relationship of kills by multiple players between Chinese teams and American teams decides the final winning side.

Importance of Tactical Awareness: Integrating Indicators Closely Connected to the Effective Predictor

The previous analysis illustrated that kills by multiple players is an effective predictor of victory in Dota 2. Simply cooperating well during fighting is not sufficient to improve kills by multiple players. The indicators closely connected to kills by multiple players are also critical. A team can only adequately prepare for successful combat by addressing these basic indicators. Therefore, we concentrated on identifying the indicators that have a strong relationship with kills by multiple players in this part. The results of this part address Research Question 3.

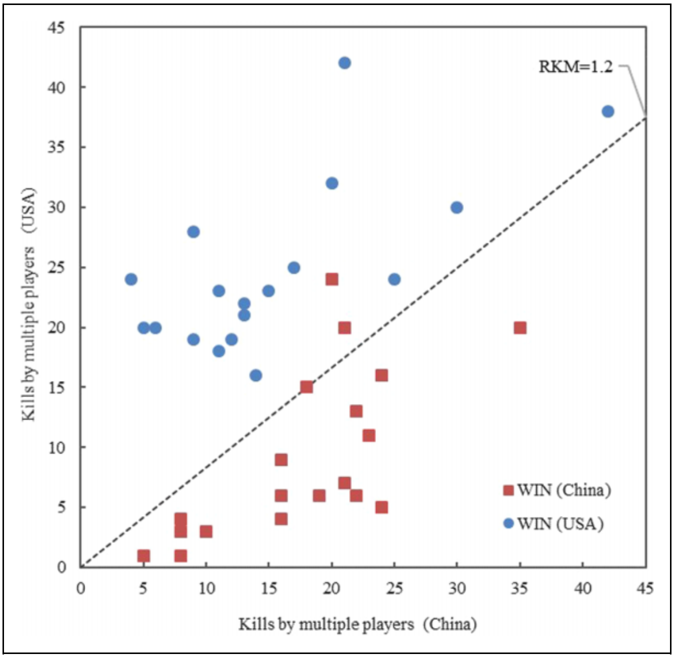

Figure 6. Scatterplot of kills by multiple players for the two countries with ratio of kills by multiple players as the auxiliary line.

Correlation analyses were first conducted to examine the relationship between these game variables and to verify the importance of tactical awareness in combat. Table 4 is the correlation matrix of the nine variables. The correlation for initiating fights and kills by multiple players is .6, which indicates that the two variables have a strong connection. The other three variables, using observer wards, activating runes, and last hitting, have approximately the same correlations with kills by multiple players. In addition, using observer wards has a strong correlation with both using smoke of deceit and activating runes, with correlations of .62 and .63, respectively. Another interesting phenomenon is that last hitting has a strong correlation with nearly all other variables in Table 4, which results from the game mechanics. Throughout the gaming process, a creep wave will spawn in each side's base every 30 s and rush to the opposite side through three lanes. The heroes from the two sides receive gold and experience by killing the creeps of the enemy side. Nearly all the creeps are killed by the heroes. Thus, last hitting is actually a time-based indicator. Last hitting increases over time, which is also true for other variables. Therefore, the correlation between last hitting and other variables reflects the relationship between the time indicator and other variables.

The significance of the effect of these variables on kills by multiple players should be tested via regression analysis. In the 37 matches, paired data can be

Table 4. Correlation Matrix of the Nine Variables.

Variables	Kills by Multiple Players	Initiating Fights	Using Smoke of Deceit	Using Observer Wards	Using Sentry Wards	Activating Runes	Last Hitting	Denying
Initiating fights	.69[a]							
Using smoke of deceit	.39	.54						
Using observer wards	.61[a]	.49	.62[a]					
Using sentry wards	.28	.30	.42	.47				
Activating runes	.60[a]	.56	.50	.63[a]	.34			
Last hitting	.66[a]	.70[a]	.72[a]	.78[a]	.47	.67[a]		
Denying	.21	.16	.30	.29	.22	.43	.34	
Kills by one player	.22	.40	.05	.04	.29	.26	.21	.04

[a]Indicates a strong connection between the two corresponding variables.

observed for each variable. For instance, kills by multiple players includes the kills by multiple players of Chinese teams and the kills by multiple players of American teams. Specifically, there are 74 data sets without considering the country indicator. Based on these sets of data, a linear regression was conducted with kills by multiple players as the dependent variable and the other eight variables as the independent variables. The variable selection method was backward. The results in Table 5 show the significance of each variable.

The goodness of fit was 0.618. In the regression, variables related to operational details, such as kills by one player, last hitting, and denying, were all eliminated, whereas the significant variables were all related to strategic tactical elements such as initiating fights, using smoke of deceit, using observer wards, and activating runes. These remarkable variables function together and influence kills by multiple players. The results further clarify the importance of tactical awareness in Dota 2.

According to the regression test results, a schematic map was created to show the kills by multiple players-centered relationships of these variables (Figure 7). This map shows that the variables related to kills by multiple players all fall within the tactical awareness category, which demonstrates that the indicators of tactical awareness have a closer relationship to kills by multiple players than do the indicators of operational skills.

Discussion

The research of Drachen et al. (2014) coincides with the conclusions of the present article. Those researchers investigated spatio-temporal team behaviors at different

Table 5. Regression Results with Kills by Multiple Players as the Dependent Variable.

Variables	Coefficient	t	Significance
Initiating fights**	.945	5.422	.000
Using smoke of deceit**	−.963	−2.054	.044
Using observer wards**	.750	3.414	.001
Activating runes*	.365	1.820	.073
Constant	−.480	−0.261	.795

Note. Independent variables are kills by one player, initiating fights, using smoke of deceit, using observer wards, using sentry wards, activating runes, last hitting, and denying. The variable selection method is backward.
*Indicates significance at the 10% level. **Indicates significance at the 5% level.

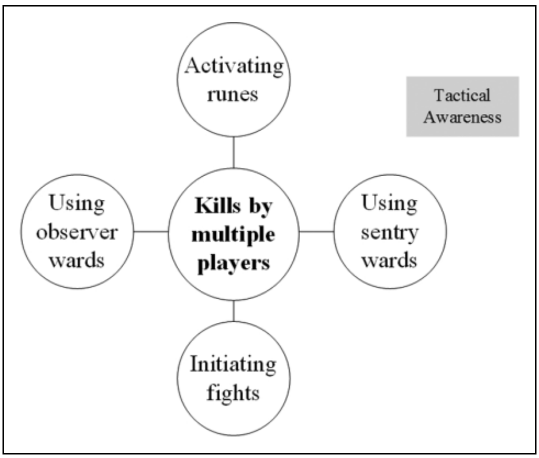

Figure 7. Kills by multiple players-centered relationship: kills by multiple players, activating runes, Using observer wards, Using sentry wards, and initiating fights all belong to tactical awareness.

skill levels. In their study, matches were divided into four levels based on matchmaking ratings, which is a metric that valve uses to sort players of the same skill level for matchmaking purposes. The four brackets were normal tier, high tier, very high tier, and professional tier. The game map was divided into 11 zones by terrain type. The results showed a difference in the number of zone changes per minute across the four skill tiers, with the professional tier seeing the most zone changes per minute. The same pattern was observed when considering winning and losing teams across the four skill tiers. The average team distance decreased with increasing skill tier. Specifically, the team members of high-level teams kept themselves at a close distance.

Thus, from the perspectives of zone changes and screening out the effective predictor in the present article, team coordination and cooperation are main indicators in predicting the game result. Moreover, achieving the goals of high-frequency zone changes, low average team distance, and a relatively large kills by multiple players requires timely assistance by team members. Therefore, it is crucial for team members to cooperate with each other and ensure that all behaviors remain aligned to the tactical goals of their team.

Although similar conclusions were obtained in these two studies, kills by multiple players involves some tactical elements that are separate from the expression of team cooperation. Associated with many other indicators, kills by multiple players is actually the last link of specific combat. As shown by the regression results, another four elements of tactical awareness are strongly correlated with kills by multiple players and constitute the entire tactical strategy of a team. It is of great importance to facilitate all-around arrangement of all these elements pertaining to tactical awareness.

A similar discussion was presented by other scholars regarding the importance of tactical awareness in Dota 2 and other MOBA games from different perspectives. Donaldson (2015) emphasized metagame expertise in League of Legends from three perspectives: the choice of team lineup, the assignment of the lanes, and the development of the campaign strategy. He noted that popular strategy types include “assassin metagame” and “split-push metagame.” In his research, a professional team typically allocates heroes of different styles to the lanes that match their characteristics and creates effective warfare schemes based on the level and fighting style of the opponents from the official website to maximize their advantages.

The present article illustrates that professional teams focus more on tactical awareness and team combat than other indicators. They monitor changes in their surroundings and create favorable conditions for themselves. In addition, operational details take a back seat to combat victory, especially in competitions among professional players.

However, compared to American teams, Chinese teams focus more on denying, a basic operational detail. Figure 8a shows the density plot of denying for winning teams and losing teams, and Figure 8b shows the density plot of denying for Chinese teams and American teams. There is no difference in the position of the two lines in subfigure a; however, in subfigure b, the red solid line is to the right of the blue dashed line, meaning that the denying rate of Chinese teams is significantly higher than that of American teams. As an operational detail, the Deny behavior is not particularly important for victory in Dota 2. The Deny behavior of Chinese teams has only a slight effect on final victories. Therefore, Chinese teams should reallocate their effort to tactical indicators, such as vision control and team coordination, in the daily training process.

Conclusions and Further Study

MOBA games are the most popular video games in the world and represent the main choice of many eSports tournaments. International Dota 2 competition holds the record for the most prize money in the eSports industry. In the present study, we

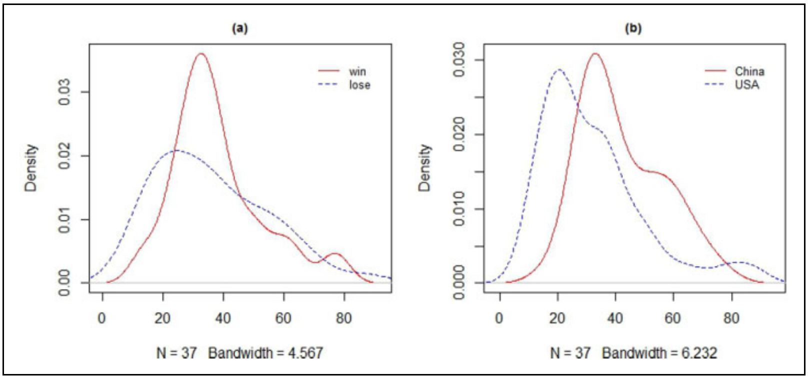

Figure 8. Density plot of Denying. (a) Density plot for winning and losing teams. (b) Density plot for Chinese and American teams.

examine the effective predictor of victories in Dota 2 between Chinese teams and American teams using data from replays of TI4 matches. The results show that kills by multiple players is an effective predictor that relates to outcomes of Dota 2. A match victory is obtained from the combined impact of kills by multiple players and other tactical indicators that are closely related to kills by multiple players such as using observer wards, activating runes, and initiating fights. A team with perfect tactical awareness performs dynamic detection of the environment and creates favorable conditions for their attacks. Then, the team initiates a fight at the appropriate moment and executes team combat and team killing, which is the most critical link.

This article explores a new method of studying Dota 2 and other relevant games and proposes a set of evaluation indicators with corresponding observation criteria that reflect the differences between winning and losing teams. From the perspective of team cooperation and team strategies, this article presents an initial framework for classifying games indicators and distinguishes the effective predictor, which can be generalized to the larger world of gameplay and sports play for developing team strategies. In addition, we present some further research directions. The present study mainly concentrates on in-game factors and strategies without considering the relationship between the players in the real world and some human factors such as fatigue and morale. Further studies can be conducted to further analyze relevant aspects. Combined with cross-cultural theories, it is of great significance to explore how the effective predictor is affected by cultural differences, which is also a research aspect of future study.

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