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Beyond Skill: Predictive Modeling with Individual and Team Attributes in League of Legends

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Abstract

The goal of this study is to explore the predictive capability of several psychosocial variables, such as personality and group cohesion, towards determining multiplayer online battle arena game outcomes - namely diversity, cohesion, and resilience, on collective performance. Our study finds that measures of individual and team perceptions of qualities provided a useful precursor for match victory. Using individual-level attributes, our cohesion survey questions provided the highest predictive value, and higher levels of perceived cohesion were associated with higher victory odds. In light of our results, we discuss the implications of using behavioral data derived from online games and opportunities for future large-scale game data collection.

Keywords: virtual teams; cohesion; cooperation; online games

Introduction

The current popularity of Multiplayer Online Battle Arenas (MOBAs) is a largely untapped data source for researchers interested in studying individual and team behavior at-scale, one which offers the chance to gather large amounts of data from a highly polished and engaging interactive team-based task. MOBAs frequently offer openly available estimates of objective player skill through published competitive rankings, they collect on average a half-hour's worth of task information metrics per game from anywhere between 2 to 10 players, and function applied problem-solving team-based tasks within research frameworks of teamwork, communication, cognitive engagement, and decision making processes (Ducheneaut, 2010).

Using online games as a means of evaluating social science research questions is of interest for several reasons. The prevalence of ubiquitous computing is quickly resulting in online interactions as a norm rather than a novelty. Using a game for research purposes provides a useful tool for matching online team-based behaviors to real-world based teams (Williams, 2010). We are also interested in how pertinent qualities may be estimated using relatively noisy signals and, consequently, be used in large-scale human behavioral analysis. Concentrating on team behavior allows us to base online derived signal choices on real-world studies, allowing researchers to utilize a large body of research that demonstrates the effects of team composition on workplace (Stewart, 2006), sports (Ingham et al., 1974), and social groups (Hill, 1982). Such compositional effects are often hard to avoid in most real-world team settings but the unique nature of competitive games lends itself to the controlling of individual differences, as such games attempt to match players with similarly skill level players by use of win/loss ratio ELO metrics (Neumann et al., 2011). Such win/loss outcomes are used in a prior study by the authors on this subject as well as within this work, mirroring the historical use of such metrics as a predictive criterion in the realm of chess (Masud et al., 2015).

In a concurrent study using the MOBA game League of Legends (LOL), we predict the winning team of a match by forming a predictive model which utilized team compositional attributes of team cohesion and diversity (Briscoe et al., under review). The game LOL itself is one of the largest competitive games played at this time (Tassi, 2014), involving teams of 3-5 players competing against another team of identical size by controlling the offensive, defensive, and support abilities of in-game character avatars over an average match length of 30 minutes (Harold, 2017).

Although our prior study was able to utilize LOL's publically large API data source to predict match outcomes, we were limited in our ability to explore the nature of subjective reports of players about themselves and their team. The current study serves as an exploratory analysis to determine the potentially useful contributors to match victory, as a both a precursor to an inferential approach and a

Table 1. Administered survey items adapted from the Group Environment Questionnaire

Question	Mean	SD
ATGS	**9.2**	**4.43**
"I did not enjoy being a part of the social aspect of this team"	6.95	2.45
"I would want to play with members of this team again"	3.68	2.6
ATGT	**14.93**	**7.61**
"I'm unhappy with my team's level of desire to win"	6.61	2.59
"This team did not give me enough opportunities to improve my personal performance"	6.43	2.58
"I did not like the map we played on"	4.21	2.73
GIT	**18.06**	**8.07**
"Our team was united in trying to reach its goals for performance"	6.99	2.13
"We all take responsibility for any loss or poor performance by our team"	7.02	2.32
"Our team members had conflicting goals for the team's performance"	3.11	2.62
"Our team members did not communicate freely about each member's responsibilities"	3.74	2.62

means of determining the variables that we map those we passively collect from game data.

In our prior analysis, our measures included the influential factors of team cohesion (Evans & Dion, 1991; Spink, 1990), team diversity (Bell, 2007; Harrison, Price, & Bell, 1998), and team resilience (Alliger et al., 2015). Our measure of cohesion was represented by a density function influenced by how many times players had played with each other in the past, the degree of matched expectations (appropriate placement, actions of other teammates), and the outcome of team cohesion as captured by game assists (helping a teammate to eliminate an enemy). We calculated diversity using distance calculations of the game's characters' fixed attributes from one another, each player's average deviance in their own character selection choices, and a measure of the number of unique teammates encountered. Resilience was calculated by calculating the amount of combative ground retaken after a loss. Taken together, we found that historical character diversity was inversely predictive of win likelihoods, while team cohesion provided a relatively strong metric for win likelihood. Resilience, as we originally calculated it, was not found to meaningfully relate to any other construct in this task environment.

Method

Game

League of Legends is an online game where each player in a match controls a single champion. In the default game mode, Summoner's Rift, two teams of five champions play one another with the goal of destroying the opposing team's nexus, which is guarded by three lanes of towers. Each champion begins at level 1. To power up to a level sufficient enough to take on the enemy's base, a champion must first focus on killing AI minions for gold and experience, later shifting to killing minions and then to destroying opponents' towers. Each match is discrete, with all champions starting off fairly weak but increasing in strength by accumulating items and experience over the course of the game. Each champion has a cooldown reduction which determines the amount of time before an ability can be used again after activation, by a percentage.

Sample

A total of 141 individuals participated using a hybrid model of in-person (n = 78) collection and online (n = 63) data collection methods. In-person participants were tested at a local gaming establishment, Battle and Brew, and online participants were coordinated using the Discord communication application. Participants were treated as one sample within analyses, as the interactive tasks during gameplay, survey response format, and communications between other players (in-game text) were identical between collection methods. A total of 19 participants provided gameplay data but did not complete one or both of our survey instruments and were excluded from analysis, forming a final predictive sample of N = 122 (in-person n = 78; online n = 44). Consent was obtained for all participants before data collection began. Overall, participant ages centered about the young adult range (M=22.50, SD=3.56), identifying as nearly entirely male (n = 121) and interested in women (n = 120). Participants were primarily either White (n = 51) or Asian identified (n = 63), most reported spiritual beliefs under the categories of Atheist/Agnostic (n = 60) and Christian (n = 47), and with a highest achieved education of primarily high school (n = 68) and bachelor's degrees (n = 52). Participants reported knowing others on their team (n = 28), the other team (n = 19), and on both teams (n = 14) before the study, an effect our sample reported as socially commonplace in this type of competitive game.

English fluency was a prerequisite for participation and only a small portion of the sample reported it as not being their first language (n = 35). The distribution of participant income was found to be unusually high for a United States sample with an average age of 22.5, with 51% (n = 62) of the sample reporting making above $35,000, 59% of that subset (n = 30) reporting to make above $95,000. Finally, our sample of participants indicated that their ideal gaming environments (n = 86 Normal Light/Low Background Activity; n = 44 Low Light/Low Background Activity) matched their typical gaming environments (n = 89 Normal Light/Low Background Activity; n = 40 Low Light/Low Background Activity), suggesting that players choose or modify their gaming environments to fit their preference for recreation.

Measures

Big Five Inventory-10 (BFI-10): The BFI-10, developed by Rammstedt and John (2007), is a 10-item version of a longer 44-item inventory developed and tested in both English and German languages and is compared against the 5-factor inventory (NEO-PI-R). The BFI-10's English test items demonstrated adequate retest reliability (μ = .72), suitable structural validity (μ = .11), and convergent characteristics (*μ of correlations to NEO-PI-R* = .52). The inventory is also reported to perform better than similar item length personality inventories (Rammstedt & John, 2007). The 10 items consist equally of negatively and positively valenced items and, after reverse scoring, each pair is added together to estimate a factor score.

Group Environment Questionnaire (GEQ): The GEQ was developed by Carron, Widmeyer, & Brawley (1985) as a measure of group cohesion. The instrument has been continually refined since its original use (Brawley, Carron, & Widmeyer, 1987; Carron, Brawley, & Widmeyer, 2002; Eys, Carron, Bray, & Brawley, 2007). The survey questionnaire has been described as a useful tool for examining the task and social cohesion of teams (Dion, 2000). The tool has a total of four scales, Individual Attractions to the Group with Social (ATGS) and Task (ATGT) components, and Group Integration at Social (GIS) and Task (GIT) levels. As our research utilized newly-created single-meeting teams, the subscale GIS was omitted in our survey, as prior group integration at the social level could not have occurred. To better fit the nature of the experimental task, we further modified the items to better capture the task domain of inquiry (e.g. changing 'I did not like the style of play on this team' to 'I did not like the map we played on'), with a full presentation of these questions presented alongside descriptive information in Table 1.

Materials

League of Legends (LOL): A wide array of game options are available for customizing the conditions of gameplay by players. In our study we chose to have game matches on the 'Twisted Treeline' map, which uses two teams of three players for a faster gameplay experience than the more traditional 'Summoner's Rift', which uses two teams of five players. Our rationale favored the former due to reductions of match time (leading to an average of two games within the scheduled time) as well as fewer difficulties scheduling participants. Most participants reported rarely playing this map type, potentially reducing the impact of prior skill involving map knowledge.

Self-reported skill and Cohesion: Based on our review of LOL as a gameplay task, we designed a series of 29 questions oriented around self and other-based estimates of gameplay abilities, actions, and teamwork to represent self-reported skill. A series of 12 questions were generated around self and other-based estimates of cooperative behaviors, including anticipating each other's actions and assisting one another. Questions were presented on a 7-pt Likert scale format ranging from Strongly Disagree (1) to Strongly Agree (7). Responses were chosen by dragging response sliders to whole number responses. As we had no reason to assume each created item would have an equal loading upon self-reported skill, our reliability analyses utilized Guttman's lambda-6. Our reliability for the self-reported skill scale (Λ = .86) was found to be higher than a standard Cronbach's alpha estimate (α = .61), demonstrating a sufficient internal consistency with differential loadings for this instrument. Our reliability estimates for our cohesion scale (Λ = .89, α = .83) possessed a similar pattern. In both cases, particularly for self-reported skill, a higher value for lambda-6 than for Cronbach's alpha supported our assumption of unequal item loadings.

Secondary measures of in-game performance: Based on our prior study and interview work with LOL players, we utilized an existing external measure of player skill, coupled with a created estimate measure based on available in-game data. Our first measure was a generated approximation for actions-per-minute (APM), a common estimate for player skill in similar game genres ("Actions per minute", n.d.), calculated as the amount of time a player spent in cooldown (number of skill activations * skill activation cooldown) for each skill slot. These were also aggregated and standardized by match time ($\sum$ (cooldown total times in seconds for each skill) / total game time in seconds) to create a measure of what ratio of game match time was spent using and/or waiting on character skill cooldowns. Additionally, we utilized an online skill ranking site for LOL players (www.LOLKING.com), which publically shows a calculated skill value similar to the internal (and unavailable to view) LOL matchmaking system skill values.

Analysis

Personality scores derived from the BFI-10 (μ = .39, SD = .94) are listed for factors of Openness (μ = .88, SD = 1.68), Conscientiousness (μ = .54, SD = 1.51), Extraversion (μ = .09, SD = 2.13), Agreeableness (μ = 1.05, SD = 1.57), and Neuroticism (μ = -.52, SD = 1.83). GEQ scores for our sample using our adapted version are listed in Table 1 alongside the adapted questions.

The predictive models consistently utilized a simultaneous entry, multiple logistic regression analysis. A total of four predictive models were tested to predict match victory outcomes using in-game measures and our included survey scales. Analyses focused in all cases on using main effects without interaction terms, as our sample size (N = 122), taken with the number of predictors tested, was not sufficient to prevent a significant risk towards overfitting the regression models. All models tested are listed in Table 2. The first analysis utilized the primary in-game performance metrics of the number of enemy kills, number of assists with enemy kills, and number of friendly deaths. These primary predictors were each uniquely and independently predictive of match victory (Model: X^2 (3) = 241.21, p < .001, -2LL = 58.23, R^2 = .90), and is largely expected based on the design of the game, and served primarily as a confirmatory and comparative analysis.

model supported the use of a subset of these predictors (Model: X^2 (7) = 17.28, p < .05, -2LL = 208.24, R^2 = .11) shown in Table 2. Both match time in cooldown and player skill rankings were unique predictors, as well as the time spent in cooldown for skill #4 (which itself was used to construct match time in cooldown). The emergence of skill #4 is not wholly unexpected as this skill represents each champion's most powerful ability (typically with the longest cooldown) which can easily change the course of a fight or match compared to other skills. All other individual skill cooldowns (skills #1-#3) were not found to be significant (p > .05). Overall, the secondary measures model provided a weak accounting of victory outcomes.

Next, we examined the included survey scales at both an individual and team level analysis level. The third analysis utilized the responses to our survey scales from each individual player (Model: X^2 (7) = 34.24, p < .001, -2LL =

Table 2. Analysis results from in-game metrics and survey-based factors

Metric	B	SE	β	95% CI	Wald X2	p	Model R^{2***}
Primary In-Game Metrics							.897*
Enemy Kills	0.53	0.12	1.7	1.34, 2.16	18.87	<.001*	
Assists with Enemy Kills	0.74	0.15	2.09	1.56, 2.79	24.96	<.001*	
Friendly Deaths	-1.15	0.22	0.32	.21, .49	27.83	<.001*	
Secondary In-Game Metrics**							.112*
Match Time in Cooldown	46.6	25.2	1.6×10^{20}	.06, 4.5x10	3.43	>.05	
LOLKING Player Ranking	0.001	0.001	1.001	1.00, 1.002	5.65	<.05*	
Time Skill #4 in Cooldown	-0.001	0	0.999	.998, 1.00	3.86	<.05*	
Survey Scales: Individual Level							.244*
Total Self-Reported Skill	-0.11	0.04	0.89	.83, .97	7.74	<.01*	
GEQ: ATGS	0.01	0.1	1.02	.83, 1.24	0.02	>.05	
GEQ: ATGT	-0.12	0.08	0.89	.77, 1.03	2.38	>.05	
GEQ: GIT	0.11	0.04	1.11	1.03, 1.20	7.44	<.01*	
Total Cohesion	0.52	0.14	1.68	1.28, 2.20	13.82	<.001*	
Extraversion	-0.19	0.09	0.83	.70, .98	4.85	<.05*	
Agreeableness	0.15	0.11	1.16	.94, 1.45	1.87	>.05	
Survey Scales: Team Level Averages							.512*
Team Avg. Cohesion	1.25	0.45	3.48	1.45, 8.35	7.8	<.01*	
Team Avg. S.R. Skill	-0.36	0.13	0.7	.54, .91	7.24	<.01*	
Team GEQ: ATGS	0.05	0.28	1.05	.60, 1.83	0.03	>.05	
Team GEQ: ATGT	-0.2	0.22	0.82	.53, 1.26	0.83	>.05	
Team GEQ: GIT	0.37	0.13	1.44	1.11, 1.87	7.64	<.01*	
Team Avg. Extraversion	-0.53	0.23	0.59	.37, .94	5.04	<.05*	
Team Avg. Agreeableness	0.64	0.33	1.9	.99, 3.64	3.77	>.05	
* Significant value, using p < .05 criteria.							
**Skill numbers 1-3 are omitted from this chart as estimates did not provide value changes larger in magnitude than the one thousandths unit decimal place.							
***Pseudo R^2 statistics are calculated using Nagelkerke's R^2 estimate.							

The second analysis utilized the generated secondary game performance metrics. Match time spent in cooldown was rescaled for regression analysis by multiplying by 100 (M= .03, SD = .03) to generate in-range regression outputs for an originally small variable (M= .00033, SD= .00029). The

199.52, R^2 = .24). The scale of cohesion produced the largest change in log-odds (1.68), followed by extraversion (.83), GEQ: GIT (1.11), and self-reported skill (.89) among significant predictors; highlighting the importance of group cohesion and teamwork with slight effects found which favor

introverts and those who self-report their skills more conservatively.

The fourth analysis included the same survey scales included in the third model, but used team level averages. To generate this model, averages for each survey scale for each team were calculated to make a single team level average which was regressed on match victory (n = 69 teams). This model was found to be significant (Model: X^2 (7) = 33.41, p < .001, -2LL = 62.11, R^2 =.51), and provided a greater degree of predictive ability than the individual predictor model. Again, the scale of cohesion provided the largest change in log-odds (3.48), followed by GEQ:GIT (1.44), extraversion (.59), and self-reported skill (.70) among significant predictors. Based on these findings, a substantial impact of match victory outcomes can be tied to the average team cohesion, followed by averages of team traits such as agreeableness and introversion, group integration with the task, and more conservative estimates of skill.

Exploratory Analysis

To further refine our instruments for future work, we performed a series of exploratory analyses on our survey questions to further identify useful dimensions of variance for future work. Using the survey dimensions of personality, cohesion, and self-reported skill, we ran a series of principal component analyses to identify which dimensions of the survey instruments contributed meaningfully to match victory. In total, we identified two meaningful dimensions involving personality and three dimensions each for cohesion and self-reported skill using scree plot observation, proportion of variance accounted for, and the distribution of item loadings for each factor.

After weighting the original survey variables by their respective factorial loadings, we regressed these weighted items towards match victory using the same method previously used. An overall summary of these analyses is reported in Table 2. At the individual level (Model: X^2 (8) = 43.90, p < .001, -2LL = 187.47, R2 = .31), a single predictive factor for personality emerged with two predictive factors for cohesion and no predictive factors (p > .05) for self-reported skill or for higher level factorial dimensions. At the team average level, while our model found significance (Model: X^2 (8) = 91.96, p < .001, -2LL = 194.62, R2 = .48), only the second factor of cohesion emerged as a significant predictor. These significant factors were composed of items centering around "..is outgoing, sociable" (-.51), "..is reserved (.45), and "..tends to be lazy" (.43) for the personality dimension, describing a behavioral report of a socially reserved and relaxed personality. The first cohesion factor, primarily subsisted on views of anticipation ("..my team anticipated me" (-.38), "..my team would say I learned their styles of play"(-.34)) and assistance ("..my team gave me help" (-.34), "..my team would say I assisted them when they needed help"(-.30)), in a negative fashion, indicating an individualistic orientation rather than a team orientation. The second factor of cohesion, which operated at both the individual and team aggregate level, positively centered around concepts of supporting other team members ("..assisted my team when they needed help" (.34), "was not able to steer the game, but supported others who could" (.40)) and team-oriented attributions ("..our victory/loss was due to my actions" (-.44), "..my teammates would say I changed the tide of the game" (-.41)), aligning with a group based orientation for match behaviors and outcomes. Overall, these compositional elements of these factors combined with the directionality produced by the analysis in Table 2 demonstrates that a team-based orientation increases the odds of a match victory, while an individually-based orientation decreases those odds.

Discussion

Our analysis centered around predicting match victory likelihoods with the League of Legends (LOL) game by applying a collection of psychological inventories (GEQ, BFI-10) alongside a series of constructed scales (cohesion, self-reported skill), against a set of primary and secondary game performance metrics. Our investigation sought to determine what beliefs about gameplay, interactions with other team members, and personality dimensions were most amenable towards matching and explores the use of predictive metrics originating directly from game matches, derived metrics from game matches, and psychological response inventories from players and teams of players to define the features which contribute towards a successful gameplay outcome.

Our analysis of gameplay metrics yielded useful conclusions for future directions using LOL as a useful tool. Results with primary in-game metrics, the number of assists with enemy kills provided the largest predictive change per unit (β = 2.09), while enemy kills (β = 1.70) and friendly deaths (β = .32) had nearly the same predictive weighting, despite widespread beliefs in the game community regarding the importance of the first kill/death in the match (Jaw, 2017, Sangheili, 2017). These effects were also directionally straightforward, with events supporting higher team performance aligned with higher victory odds. Our secondary in-game metrics were much less robust than the primary metrics at predictions of match victory outcomes. This may be due to different contributions of skill use over time (rather than as an aggregate of the entire match), or due to the more individualistic and hero-specific nature of most of these metrics. Regardless, the small directionality in this relationship indicated higher player rankings (β = 1.001, CI: 1.00, 1.002) and lower time spent in skill#4 (player ultimate abilities) cooldown (β = .999, CI: .998, 1.00) were associated with higher victory odds.

Using measures of individual and team perceptions of qualities provided a useful precursor for match victory. Using individual-level attributes, our cohesion survey questions provided the highest predictive change (β = 1.68, CI: 1.28, 2.20), and higher levels of perceived cohesion were associated with higher victory odds. Following cohesion was a close collection of self-reported skill (β = .89, CI:.83, .97), GEQ:GIT (β = 1.11, CI:1.03, 1.20), and extraversion (β = .83,

CI: .70, .98), with lower levels of self-reported skill, higher levels of perceived group task integration, and higher levels of introversion associated with higher victory odds. The elements of Agreeableness, and GEQ: ATGT and GEQ: ATGS did not reach significance criteria (p > .05).

Conclusions & Future Work

Here we conducted an exploratory analysis to determine the potentially useful contributors to match victory. We found that factors related to individual and team perception of qualities were predictive of match victory. This work supports our view that real-world social phenomena data such as those from MOBAs can serve as accurate sources to construct and develop predictive models of group level phenomena. Ideally, we would like to ascertain whether virtual spaces provide enough realism to make them an attractive source of behavioral data and athat online games that require players to work together towards a common goal are a potentially useful analog space for building principles to understand an increasingly connected world.

Acknowledgments

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