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Effects of individual toxic behavior on team performance in *League of Legends*

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ABSTRACT

Toxic behavior in online video games is frequent and problematic. Previous research has linked toxic behavior with worsened performance. No study, however, has investigated a causal relationship between toxic behavior and worsened performance, nor investigated potential moderators such as individual motivation. Using 716 players of League of Legends, a popular team-based video game, the effect of toxic behavior on performance and the influence of motivation was assessed. Players were exposed to either a control condition where a confederate behaved neutrally or an experimental condition where a confederate operationally "flamed" participants. Performance statistics were gathered from the NA.OP.GG database. Motivation was self-reported after matches ($N = 139$). Toxic behavior significantly worsened the multivariate vector of team and individual performance. Motivation influenced baseline individual performance but did not significantly moderate the effect of toxic behavior on individual performance. These results encourage individuals to refrain from engaging in online toxic behavior and provide motivation for gaming communities to take steps to decrease toxic behavior. Future research should take a closer look at the role of individual differences and underlying cognitive processes involved in toxic behavior.

Introduction

In 2013, 1.2 billion people were playing video games, with 700 million of those playing online games: roughly 10% of the world's population (Population Reference Bureau, 2013; Spil Games, 2013). By 2018, that number had more than doubled to 2.5 billion (WePC, 2018). This represents an enormous amount of growth in just five years, as now around one in three (32.9%) people play online video games (World Bank Group, 2019), and are therefore involved in online gaming environments and communities. As these environments are becoming increasingly common, it is important to study the social interactions that occur among players within online video games and the effects of these interactions.

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It is of concern, then, that online gaming environments are notorious for their antisocial and offensive behaviors (Holz Ivory et al., 2017). Specifically, although social interactions within these environments are considered important and meaningful to gamers, (Cole & Griffiths, 2007; Holz Ivory et al., 2017), 70% of gamers aged 18–24 report being harassed online, and 62% of respondents classified online harassment as a major problem (Duggan, 2014, 2018). Harassment and other forms of antisocial behaviors online are generally referred to as toxic behavior (Suler, 2005), which encompasses several types of highly nuanced behaviors across different online environments. Examples of toxic behaviors include cyberbullying, griefing, mischief, sexism and sexual harassment, trolling, cheating, and flaming (Foo & Koivisto, 2004; Fragoso, 2015; Joinson, 1998; Kwak, Blackburn, & Han, 2015; March & Marrington, 2019; Neto, Yokoyama, & Becker, 2017; Tang, Reer, & Quandt, 2019; Turnage, 2007).

The prevalence of toxic behavior has long posed challenges for gaming developers, as toxic behavior is complex and multifaceted, and does not extinguish with simple punishment (Blackburn & Kwak, 2014; Donaldson, 2017; Foo & Koivisto, 2004; Kwak et al., 2015; LeJacq, 2015; Warner & Raiter, 2005; Watson, 2015). In the hopes of promoting a healthier social environment among their player base, Riot Games, creator of *League of Legends*, one of the world's most popular video games (Tassi, 2016), explored the relationship between toxic behavior and performance in *League of Legends* (Carlson, 2013). They reported a positive correlation between game losses and toxic behavior, noting that, on average, teams with no toxic players had a 54% chance of victory, whereas teams with three toxic players had a 46% chance of victory. These findings were later expanded to show that toxic behavior was correlated not only with less desirable outcomes, but also with decreased indicators of performance (Neto et al., 2017). These results were interpreted and presented by Riot Games as evidence for players to refrain from being toxic toward other players.

However, while Riot Games explicitly sought to disincentivize toxic behavior by pairing it with undesirable outcomes and worsened performance, they were limited by their correlational design. The association between toxic behavior and performance may not be a compelling argument for refraining from online toxic behavior, as toxic behavior might be a reaction to, rather than a cause of, poor performance. In the interest of better understanding the effects of online toxic behavior and supporting the general social health of online environments, we sought to assess the directionality of this association between online toxic behavior and performance by exploring differing predictions from psychological theory, experimentally manipulating confederate toxic behavior, and measuring resultant team and individual performance.

Poor performance worsens behavior: a self-determination theory perspective

One explanation for the association between online toxic behavior and performance is that people react toxically to poor performance. For this purpose, self-determination theory (SDT; Ryan & Deci, 2000) is ideal and is commonly used when investigating aggressive behavior and media interaction (Demircioglu, 2018; Przybylski, Deci, Rigby, & Ryan, 2014). At its core, SDT posits that people are driven by three basic needs: the need for competence, the need for autonomy, and the need for relatedness. People are highly motivated to satisfy these needs, and satisfaction of these needs provides the foundation for broader psychological wellbeing. In contrast, thwarting or threatening these needs, either situationally or chronically, prompts frustration and aggression (Ryan, Rigby, & Przybylski, 2006). In this sense, SDT builds upon the frustration-aggression hypothesis (Berkowitz, 1989), which has demonstrated that frustration and hostile aggression are incited when faced with barriers to desired goals (Dodge & Coie, 1987), by redefining goals as the pursuit of self-perceptions of competence, relatedness, and autonomy. Especially in team environments, individuals are vulnerable to threats to these needs from the poor performance of others. Poorly performing teammates directly inhibit the individual ability to perform well and the likelihood of winning, both of which are integral to competence need satisfaction. Therefore, poorly performing teammates are expected to elicit approach-oriented emotions like anger and frustration from other teammates (Carver & Harmon-Jones, 2009). In other words, we may expect that the association between toxic behavior and poor performance is primarily driven by poor performance inciting toxic behavior.

These claims are well supported in research in online gaming environments. For example, previous studies experimentally demonstrated that competence-impeding gameplay in video games increases instances of aggression and toxic behaviors (Przybylski et al., 2014), and that game outcomes are related to post-game expressions of aggression, such that players who lose are significantly more likely to engage in post-game aggressive behaviors (Breuer, Scharkow, & Quandt, 2015). In addition, Kasumovic and Kuznekoff (2015) found that occurrences of toxic behavior amplify when the frustrated player themselves is also playing poorly. In other words, when individual competence is clearly threatened, either by teammates or by circumstance, frustration and resultant toxic behaviors are more common.

According to this perspective, poor performance may cause toxic behavior. If poorly performing teammates are truly perceived as competence-impeding by players, toxic behavior is the expected reaction. However, a competing body of evidence also suggests that the association between toxic behavior and performance may yet better be explained in the opposite direction, such that toxic behavior causes poor performance.

Toxic behavior worsens performance: a bad apple perspective

Another explanation for the association between online toxic behavior and performance is that online toxic behavior worsens performance. In this sense, the "bad apple" theory is useful, as it is immediately concerned with the effects of negative and toxic behaviors on performance (Felps, Mitchell, & Byington, 2006). Broadly, Felps and colleagues depict the ability of even a single group member, referred to as a "bad apple," to disproportionately disrupt group- or team-level performance by engaging in certain types of undesirable behaviors, such as withholding effort, continually expressing negative affect, and violating interpersonal norms. "Bad apple" theory elaborates on violating interpersonal norms, specifically, by identifying seven common forms of interpersonal norm violations: making fun of someone, saying hurtful things, making inappropriate religious or ethnic remarks, cursing at others, playing mean pranks, being rude, and publicly shaming others. These "bad apple" behaviors elicit negative psychological states in other team members, such as feelings of inequity, negativity, and reduced trust, which, in turn, disrupt performance by prompting withdrawal and behavioral retaliation. Therefore, we may expect that the association between toxic behavior and poor performance is driven by the toxic behaviors directly harming group performance.

Related research supports this proposed directionality of causation in online environments. Specifically, research has demonstrated that online toxic behavior elicits toxic (Neto et al., 2017) and spiteful (Yip, Schweitzer, & Nurmohamed, 2017) retaliation in others, which, in turn, is associated with worsened collective performance. Furthermore, toxic behavior has been demonstrated to damage trust and team cohesion in online environments, which are useful indicators of team performance (Carron, Colman, Wheeler, & Stevens, 2002; Lee & Chang, 2013; Tseng, Ku, Wang, & Sun, 2009). In addition, although the "bad apple" theory is typically used to describe workplace performance, all three "bad apple" behaviors (withholding effort, continually expressing negative affect, and violating interpersonal norms) can be immediately recognized as online toxic behaviors, as these exact behaviors have long been observed in abundance online (Holz Ivory et al., 2017; Joinson 1998; Kiesler, Siegel, & McGuire, 1984). Given that various elements of online environments (such as anonymity, invisibility, etc.) seem to facilitate the prevalence of these behaviors online (Christopherson, 2007; Kwak et al., 2015; Lapidot-Lefler & Barak, 2012; Suler, 2005), these "bad apple" effects are likely commonplace in online team-oriented environments.

According to this perspective, toxic behavior may cause poor performance. Therefore, players may benefit from refraining from engaging in toxic behavior toward teammates, as toxic behavior may negatively affect the performance of teammates. However, randomized experimentation is still required to test this relationship, and the following question remains: If toxic behavior truly hurts performance, who is more likely to be negatively affected by toxic behavior? As to this point, we have assessed the literature predicting the effects of toxic behavior on performance and the effects of poor performance on teammates, but we have not investigated the potential effects of individual differences in those who are targeted by toxic behavior. In other words, if toxic behavior may worsen performance, are certain people more likely to suffer performatively? To investigate this question, we must assess the potentially moderating role of motivation and individual differences.

Motivation and individual differences

In exploring the association between toxic behavior and performance, specifically while considering SDT, it is important to assess the role of individual differences. Toxic behavior is ultimately a subjective experience, especially given how the intentions of those engaging in toxic behaviors are often ambiguous (Blackburn & Kwak, 2014; Donaldson, 2017; Warner & Raiter, 2005; Watson, 2015). For example, the same set of in-game behaviors (e.g., experimenting with a set of unusual strategies) may be deemed toxic or not depending on what intent is attributed to the player (Donaldson, 2017). Attributions of intent are inferred from assumptions of character, which are often biased to reflect characteristics of the assumer (Human & Biesanz, 2011). For those who place more value in video game exploration, intent is assumed to be more genuine, and the behavior less toxic. For those who place more value in performance, intent is assumed to be more disingenuous, and the behavior more toxic. In this sense, the "bad apple" and SDT theories can be viewed as complementary: a person's own motivations can color their interpretations of others behavior, influencing whether the teammate's behavior triggers worsened performance. As such, understanding a player's motivation for playing video games is of theoretical importance for determining the attributions they make of others in-game behaviors and the association between toxic behavior and performance.

The literature on motivations for playing video games is diverse, with studies ranging from mapping more traditional psychometrics for personality, such as the Big Five (Barrick & Mount, 1991), onto gameplay motivation (Jeng & Teng, 2008) to establishing and validating distinct motives of play (De Grove, Cauberghe, & Van Looy, 2016; Yee, 2006) or establishing "types" of gamers and explaining individual preferences for different styles of video games (Scharkow, Festl, Vogelgesang, & Quandt, 2015). Different studies suggest slightly different core motivations, such as De Grove et al.'s (2016) eight motives for playing videogames (performance, narrative, social, pastime, habit, escapism, agency, and moral self-reaction) versus Scharkow et al.'s (2015) eight gaming gratifications (fantasy, competence, exploration, social capital, team play, competition, mechanics, and narration). However, across these studies, there is a relative consensus and representation of the same three overarching categories of motivation that have been demonstrated to map neatly within the tenants of SDT: Gamers tend to possess, to varying extents, motives of achievement (competence), socialization (relatedness), and immersion (autonomy) (Ryan et al., 2006; Yee, 2006). Players who identify as being primarily achievement-motivated are likely to value competence enhancing outcomes more highly. Therefore, we might expect achievement-motivated players to, by definition, perform better than other-motivated players, but perhaps they are also more likely to feel threatened by poorly performing teammates, as they may perceive poorly performing teammates as a stronger threat to their goals.

The present study

Toxic behavior is problematic in online environments, and previous correlational research by Riot Games (Carlson, 2013) and others (Neto et al., 2017) revealed an association between toxic behavior and poor performance in *League of Legends*. Riot Games interpreted this association to suggest that toxic behavior diminishes team performance. Our review of online behavioral and motivation literature suggests that this conclusion may or may not be appropriate. Therefore, we sought to assess the validity of Riot Games's conclusion and experimentally test the aligning "bad apple" theory (Felps et al., 2006) that one toxic player may hinder team performance while also examining whether teammate motivation for playing online games moderates this causal path. In line with previous research, we used *League of Legends* (*LoL;* https://na.leagueoflegends.com/en/) as the platform for our study.

Based on our review of the literature, we designed three specific hypotheses to guide our experiment:

H1: Overall team performance in *League of Legends* will decrease in the presence of a toxic confederate.

H2: Motivation for playing online games will influence individual performance in *League of Legends*, such that achievement motivated players will individually outperform players of other-reported motivations.

H3: Motivation will moderate the relationship between toxic behavior and individual performance in *League of Legends*, such that the performance of achievement-motivated players will be more negatively impacted by toxic behavior than players of other-reported motivations.

Method

Participants

Due to practical time constraints, researchers preemptively determined a sample size goal of 180 matches, involving 720 unique teammates, hereafter referred to as "participants." This number was a compromise of confederate time constraints and an a priori power analysis in G*Power for a MANOVA interaction design with two groups and four response variables that yielded a suggested sample size of N = 196 for power = .80 (Faul, Erdfelder, Lang, & Buchner, 2007). The average match length was 38.25 minutes (SD = 7.72), and our three confederates played over 114 hours of *LoL* for study purposes over four weeks (not accounting for queue times, champion select, or load-in time). A single match was later determined to have failed to meet experimental criterion (a participant failed to connect to the game) and was incorrectly recorded and dropped from analyses, leaving our total N = 179 matches with 716 participants. A two-group MANOVA sensitivity analysis in G*Power (Faul et al., 2007) with N of 179, power = .80 on four response variables indicated that we could expect to detect an effect size of 0.068. Our effect size estimate from this study was 0.063, indicating that we were slightly under-powered. These 716 participants were sampled via the online unranked match-making system in *LoL*, such that they were anonymous, random *LoL* players who happened to be searching for an unranked *LoL* match at the same time as a research confederate. As *LoL* is typically played with two competing teams of five, four participants were unknowingly matched with a research confederate per match. Therefore, each match consisted of four participants and one confederate against five other randomly matched and anonymous *LoL* players for whom no manipulation was imposed and no data were collected. Participants (N = 139; 19.4%) responded to post-game questions regarding motivation. No participant was sampled twice.

Procedure

Institutional Review Board approval was granted prior to beginning data collection. Confederates (three undergraduate male players of *LoL*, each of whom were experienced *LoL* players with over 500 hours played) queued into unranked *LoL* matches utilizing separate, unranked, level 30 accounts. These accounts were created to possess a Match Making Rating generalizable to the largest population possible within *LoL*. To minimize the impact of the con-federates themselves within matches, confederates were trained to abstain from making decisions for their teams. Confederates always followed partici-pants and complied with whatever in-game decisions participants suggested. For this reason, the confederates played the "support" position [by extension, enchanter-style supports (Janna or Soraka)] exclusively, as "supports" within

LoL are most completely and immediately dependent upon other players in the game. In addition, each confederate was comfortable playing the support role, was of comparable skill, and played an equal ratio of toxic and control games. Furthermore, confederate performances were not factored into team performance measures. Data were collected from March-April of 2017.

Immediately following the completion of matches, confederates debriefed participants in the post-game chat lobby. Following the debriefing script, confederates assessed participants using Yee's (2006) motivations for playing online video games upon receiving participant consent. As it was not feasible in the post-match chat room to present participants with the full set of 40 questions, confederates instead presented participants with descriptions of Yee's three overarching motivation categories (social, achievement, and immersion). Participants were asked to report which category best explained why they play *LoL*. These categories were presented to participants using a quick-typing script coded to the character limitations of *LoL* chatrooms, such that participants always saw all three categories simultaneously and in the same order (social, achievement, and immersion, respectively). Social motivation was explained as playing primarily to spend time with friends or making new friends online. Achievement motivation was explained as playing primarily to improve performance/mechanics and to achieve a better ranking. Immersion motivation was explained as playing the game to relax and find oneself in a new world. Confederates then thanked participants and remained in the chat lobby to answer other questions about the study, as well as provide contact information upon request.

Experimental design

Teams were assigned by a dice roll (even versus odd) into one of two different conditions of play (91 toxic, 88 control) in a between-subjects design, such that 364 participants experienced a toxic condition, and 352 a control condition. The toxic condition consisted of a toxic confederate who would "flame" participants by excessively using *LoL*'s pinging system to display symbols such as exclamation points and question marks on the screens of participants [representing extreme typographic energy, an accepted operationalization of flaming (Joinson, 1998; Turnage, 2007)]. These "pings" appeared on-screen as brief flashes of question marks and exclamation points with an accompanying unique noise that all participants could see and hear (See Figure 1). Excessive or targeted use of pings is interpreted as hostile and offensive behavior in *LoL*. Brief flurries of question mark and exclamation point pings were used approximately every two minutes per toxic condition. Confederates would ping participants' characters immediately following whatever mistakes or misfortunes arose naturally throughout the game, including death of participants or the confederate, loss of objectives to the other team, etc. Even in the

Figure 1. Toxic behavior with excessive pinging. Screenshot taken in-game in Riot Games's *League of Legends*, all rights reserved.

absence of mistakes or misfortunes, confederates would ping participants, which would suggest that they were positioned incorrectly, or not playing aggressively enough, etc. These pings were designed to suggest that confederates thought that participants were playing incompetently, representing an immediate threat to participant competence (Ryan et al., 2006) and representing Felps et al.'s (2006) descriptions of "bad-apple" behavior (violating interpersonal norms; interpretable as making fun of someone, being rude, and publicly shaming others). Aside from pinging, confederates in the toxic condition refused to communicate with participants, even when asked a direct question. During the data collection window, players could not deactivate pings from appearing on their screens, making the toxic condition unavoidable. However, as of May 17, 2017, deactivating pings is now possible within *LoL* (Perchied, Costigan, Lehman, & Moutinho, 2017). In the control condition, confederates did not initiate communication with participants, did not ping participants, and only responded when non-hostile questions were aimed specifically at them. In both conditions, confederates followed participants through gameplay and avoided decision-making.

Measures

Match statistics were recorded by a third-party website (OP.GG; http://na.op.gg) that publishes all publicly available data for *LoL*. Recorded data included match length, kill-death-assist ratio (KDA), creep score per minute (CSPM), gold per minute (GPM), gold share (GS), kill participation (KP), total damage dealt (DAM), damage per minute (DPM), objectives taken (OBJ), and objectives taken per minute (OBJPM).

Team performance

Hypothesis 1 was tested using team performance metrics to assess the effect of toxicity on team performance. Indicators of team performance were team KDA, team gold, team objectives, and team damage. Each measure of team performance is the composite of four participants. To clarify, confederate performance was not included in measures of team performance. Team KDA was all participants' kills plus all participants' assists, divided by all participants' deaths. Team gold was the sum of gold earned by all participants. Team objectives was the sum of objectives, including towers, dragons, barons, etc. captured by the team. Team damage was the sum of damage to enemy players dealt by participants each match. For all indices, higher scores were indicative of better performance. All indicators of team performance were normally distributed (skew < 2, kurtosis < 7) except for team KDA, which had to be log-transformed to account for right skew. (Curran, West, & Finch, 1996). Standardized scores were used for analyses.

Individual performance

Hypotheses 2 and 3 were tested using individual performance metrics to allow for the examination of individual motivations as a moderator on the association between toxicity and performance. Indicators of individual performance were KP, DPM, GPM, and GS. These individual performance indicators were selected to parallel team performance indicators. KP was an individual participant's involvement in the total amount of team kills, ranging from 0% to 100%. DPM parallels team DAM; it was an individual's damage dealt to enemy players per minute. GPM was likewise an individual's gold earned per minute. GS was an individual's share of the total gold owned by all teammates. For all indices, higher scores were indicative of better performance. All variables were normally distributed (skew < 2, kurtosis < 7) (Curran et al., 1996). Standardized scores were used for analyses.

Motivation

Motivation was measured using Yee's (2006) categories of motivation for playing online games (social, achievement, and immersion). These categories were created by assessing a set of 40 motivation questions in a sample of 3,000 online players. Yee's factor analysis yielded three categories of motivation (Cronbach's $\alpha > .70$). In our sample ($N = 139$), 69 participants identified as being socially motivated, 39 as achievement motivated, and 31 as being primarily motivated by video game immersion. Of these participants, 107

(77.0%) came from winning matches. We conducted equivalence tests to detect differences in response likelihood between game outcomes using the TOSTER package (Lakens, Scheel, & Isager, 2018) for R 3.6.1 (R Core Team, 2019). These tests revealed that there were statistically significant differences between response likelihood and game outcome according to Fisher's exact z-test, and that those differences are statistically not equivalent to zero when the specified smallest effect size of interest (SESOI) effect size was set to 0.1 ($Z = 0.628$, $p = .735$). However, when the SESOI was increased to 0.2, the equivalence test became statistically equivalent to zero ($Z = -2.891$, $p = .002$). This suggests that, while the difference in response rates between players who won or lost the game is statistically significant, it is only of limited practical significance. In addition, the representation of winners is not statistically different across motivation: 28 (71.8%) of achievement motivated, 26 (83.9%) of immersion motivated, and 53 (76.8%) of social motivated players came from winning matches ($\chi2(2) = 2.487$, $p = .288$).

Results

Hypothesis 1: toxic behavior predicting team performance

All analyses were run using SPSS Version 25 unless otherwise specified. To test whether toxic behavior predicted team performance, a two-group between-subjects multivariate analysis of variance (MANOVA) was conducted using four dependent variables: team KDA, team gold, team objectives, and team damage (see Table 1 for descriptives. See our OSF link in our Data Availability Statement for additional variable descriptives and correlation matrices). All variables were significantly correlated between 0.27 and 0.87, M = 0.54.

Univariate outliers were examined using the median absolution deviation (MAD; Leys, Ley, Klein, Bernard, & Licata, 2013). The MAD was 1.4826 (Huber, 1981). The rejection criteria for the MAD was set at the median ± 3 MADs. This technique uncovered one univariate outlier for team damage and seven univariate outliers for team KDA. Mahalanobis' distance yielded no multivariate outliers (Newton & Rudestam, 1999). The univariate outliers were determined to be legitimate cases (as opposed to data entry errors or misreported values). Analyses were conducted both retaining the outliers and with

Table 1. Team performance descriptives.

	Control		Experimental	
	M	*SD*	*M*	*SD*
Team KDA	4.0	4.0	3.1	2.1
Team Gold	63,606	17,764	57,189	15,523
Team Objectives	9.0	4.3	6.8	4.9
Team Damage	101,402	43,789	89,412	38,488

Raw score data presented.

the outliers truncated to the third MAD. The pattern of results was the same, and thus we retained the univariate outliers.

The Bartlett's test of sphericity was significant (approximate chi-square = 5772.83, $p < .001$), indicating sufficient correlation to continue with the MANOVA analysis. The independent variable was the condition: toxic or control. The dependent variables were team indicators of performance. Team performance was a group-level variable. The Box's *M* test was significant ($p = .011$), indicating that the observed covariance matrices of the dependent variables were unequal across conditions. The MANOVA design with relatively equal observations in each condition is robust to this violation (Tabachnick, Fidell, & Osterlind, 2001), but the more-conservative Pillai's trace was used to evaluate the multivariate effect.

The presence of a toxic confederate significantly lessened team performance (Pillai's trace = .063, $F(4,174) = 2.903$, $p = .023$, $\eta^2 = .063$. Univariate ANOVAs were conducted on each dependent measure. Analyses were run with and without time as a covariate, and the pattern of results remained the same. The results to follow excluded time as a covariate. Levene's test of equality of error variances was nonsignificant for all measures. Three univariate ANOVAs were significant (team objectives, KDA, and gold). To counter the family-wise error rate inherent in testing univariate ANOVAs, the Holm-Bonferonni step-down procedure was used to adjust the alpha level (Holm, 1979). Two univariate results remained significant: teams in the toxic condition (M = 6.80, SD = 4.85) took significantly fewer objectives (M = 9.03, SD = 4.26) and earned significantly less gold (M = 57,189, SD = 15,523) than teams in the control condition (M = 63,606, SD = 17,764); respectively:[$F(1,177) = 10.663$, $p = .001$, $\eta^2 = .057$]; [$F(1,177) = 6.636$, $p = .011$, $\eta^2 = .036$]. Additionally, we ran alternate analyses by collapsing our standardized dependent variables into a single composite and conducting an independent samples t-test. Our pattern of results remained consistent: $t(177) = 3.104$, $p = .002$.

Hypotheses 2 & 3: toxic behavior, motivation, and individual performance

Individual indicators of performance were KP, DPM, GPM, and GS. All variables were significantly correlated between 0.44 and 0.72, M = 0.59. Individual KDA and creep score per minute were considered as additional indicators but were not intercorrelated properly for the MANOVA design.

Using the MAD technique, there were five univariate outliers in kill participation, five in gold per minute, 12 in gold share. These outliers were determined to be legitimate outliers typically indicating exceptional performance. A Mahalanobis' distance test yielded no multivariate outliers (Newton & Rudestam, 1999). Analyses were conducted retaining the outliers and with the outliers truncated to the third MAD. The pattern of results was the same and so the numbers presented below retain the univariate outliers.

Individual scores were nested by match, with a maximum cluster size of four. Intracluster correlation coefficients (ICCs) were calculated for each dependent variable, where ICC = $\tau_{00}/(\tau_{00}+ \sigma^2)$ (Raudenbush & Bryk, 2002). KP and GS did not have measurable ICCs, as they were group-based variables. ICC estimates were .12 for DPM and .31 for GPM, indicating that mean differences among the matches accounted for 12% and 31%, respectively, of the variation in these two variables. ICCs were then used to calculate the design effect [1+(nj-1)ICC]. DPM yielded a design effect of 1.35, and GPM 1.94. A design effect less than 2.0 indicates that ignoring clustering will not skew results (Muthén & Satorra, 1995), and so a regular MANOVA model was fit to the individual performance data.

The main effect of motivation on individual performance was significant: Pillai's Trace = .081, $F(4,137) = 3.05$, $p = .019$, $\eta^2 = .081$. Achievement-motivated players performed better than other-motivated players (See Figure 2, Table 2). The multivariate main effect of condition on individual performance was also significant: Pillai's Trace = .031, $F(4,711) = 5.692$, $p < .001$, $\eta^2 = .031$. Levene's test was nonsignificant for all measures, and one univariate

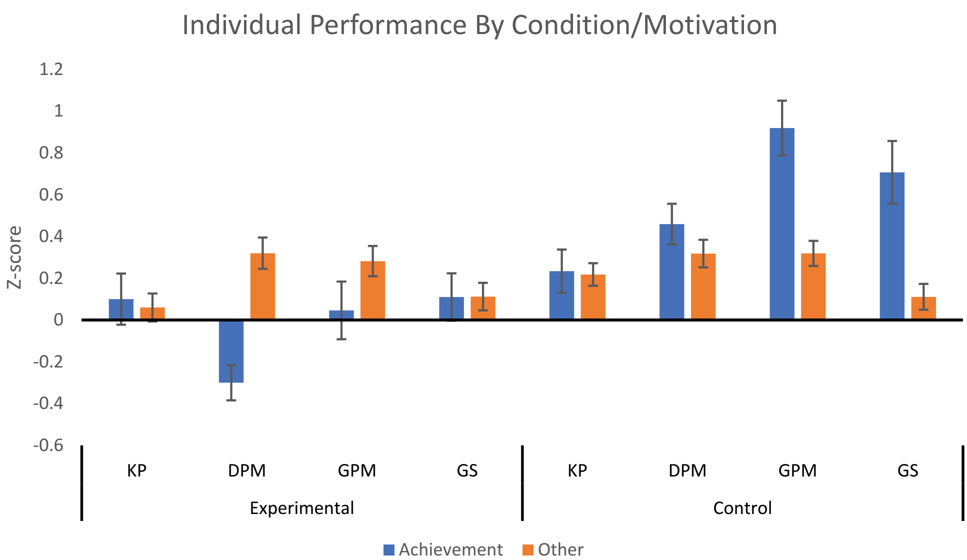

Figure 2. Individual performance by condition/motivation.

Table 2. Individual performance by condition and motivation.

	Experimental		Control	
	Achievement	*Other*	*Achievement*	*Other*
Kill participation	.10	.06	.23	.22
Damage per minute	−.30	.32	.46	.32
Gold per minute	.05	.28	.92	.32
Gold share	.11	.11	.71	.11

Standardized data presented.

result was significant: individuals exposed to a toxic teammate earned significantly less gold per minute [$F(1{,}714) = 8.898$, $p = .003$, $\eta^2 = .01$].

The effects of toxic behavior and player motivation on individual performance were tested using a two-way between-subjects MANOVA. This analysis had unequal sample sizes across conditions (toxic N = 72, control N = 67, achievement motivated N = 39, other motivated N = 101). Participants who responded to post-game questions individually outperformed players who did not respond (Pillai's Trace = 0.29, $F(4, 711) = 5.378$, $p < .001$, $\eta^2 = 0.29$), suggesting a bias in our sample. The dependent variable covariance matrices were equal across condition and motivation type ($p = .11$, Box's M). Bartlett's test of sphericity was significant (approximate chi-square = 4597.10, $p < .001$), suggesting that there was significant correlation among the dependent variables for the MANOVA design. The interaction effect of condition by motivation was not significant: Pillai's Trace = .063, $F(4{,}137) = 2.303$, $p = .062$, $\eta^2 = .063$.

Post-Hoc analyses

As we collected and analyzed our data, we observed another effect that we did not explicitly anticipate. Throughout the data collection process, another measure we recorded was surrenders proposed by participants. Within *LoL* during our experiment, at 20 minutes into the game, players were eligible to purpose surrender votes (See Figure 3). When a surrender vote was proposed, players had 60 seconds to anonymously respond affirmatively or negatively to the vote. As soon as at least four of five players on a team responded affirmatively to a surrender vote, the game immediately ended in a loss for the surrendering team. If a vote failed, the game continued, but participants were able to propose another surrender vote after several minutes. While we did not explicitly record which individual participant initiated a surrender vote, we did record instances of surrender proposals by participants. In fact, confederates had specific protocol to follow in the

Figure 3. Surrender vote interface. Screenshot taken in-game in Riot Games's *League of Legends*.

case of surrender votes: should one arise, they were to refuse to vote, as voting in a surrender proposal is a form of decision-making. Several games throughout the experiment ended in surrender, both for confederates' teams and opposing teams (unfortunately whether a game ended in surrender was not recorded by researchers or reported on OP.GG). However, participants exposed to a toxic confederate were much more likely to propose surrender votes (M = 0.56, SD = 0.87) than participants in control conditions [M = 0.30, SD = 0.61; $t(161.324) = -2.363$, $p = .019$, $d = .35$] While the literature on team performance would predict that toxic behavior would interfere with team cohesion (Carron et al., 2002), we did not preemptively reason that a surrender vote could be understood as an artifact of reduced team cohesion. However, as surrender votes represent immediate requests by participants to forfeit and move on to other games with new teammates, it can be inferred that team cohesion was reduced in the presence of a systematically toxic teammate.

Discussion

Our research was inspired by a basic correlation between two integral parts of online gaming: performance and toxic behavior. This correlation was presented in such a way to suggest that online gamers should avoid abusing their teammates to protect their own team's performance and chances of victory (Carlson, 2013). We sought to assess the validity of this conclusion by inspecting the association between performance and online toxic behavior in an experimental design. In the current study, toxic behavior decreased team performance. In direct support of predictions of the "bad apple" theory (Felps et al., 2006), the presence of a single systematically toxic confederate significantly harmed overall team performance, and post hoc analyses revealed that teams were more likely to propose surrenders in the presence of a toxic teammate, suggesting that toxic behavior may harm performance by disrupting team cohesion. This further supports the notion that toxic behavior is counterproductive to performance.

To our knowledge, our study presents the first evidence of the causal impact of online toxic behavior on team performance in an online gaming environment. Therefore, our findings support and extend the previous correlational research (Carlson, 2013; Neto et al., 2017), provide a clear and compelling incentive for players to refrain from engaging in toxic behavior, and offer insight into the complex dynamics of human interactions in online gaming environments. Considering that toxicity and performance are relevant not only to other online games (Fox, Gilbert, & Tang, 2018; Shen et al., 2020), but other online experiences as well [for example, Massive Online Open Courses (Comer, Baker, & Wang, 2015) or social media (Patchin & Hinduja, 2010)], our primary experimental finding that toxicity decreased team performance allows a variety of stakeholders to strengthen claims that toxicity causes decreased performance all around.

We also found that motivation plays a role in individual performance. Participants who reported the achievement motivation had overall better performance ratings than their other-motivated peers. These results provide evidence for the general merit of using motivational paradigms, such as SDT, to study behavior in online gaming environments. Despite this, and in contrast to expectations, we were unable to find conclusive evidence to support a moderating effect of individual motivation on toxic behavior and performance.

It is important to note that our findings do not invalidate the evidence of previous studies using the SDT paradigm that demonstrate that poor performance elicits toxic behavior (Breuer et al., 2015; Kasumovic & Kuznekoff, 2015; Pryzybylski et al., 2014). Instead, our findings suggest that the inverse relationship is additionally true instead of overridingly true. Simply because our findings demonstrate that toxically abusing teammates will cause them to perform worse does not suggest that people do not also react toxically to the poor performance of their teammates. It may be that poor performance initially sparks toxic behavior, which, in turn, worsens performance, leading to more toxic behavior, then toxic retaliation from the abused teammate, and so on.

In other words, our review supports the idea of a broader, cyclical relationship between worsened performance and toxic behavior in online gaming environments, and may tap into what is culturally understood within *LoL* and other forms of competitive gaming as "tilt." "Tilt" is a cyclical mental or emotional state characterized by self-destructive frustration, where once a player is "tilted," their performance is impeded in such a way that further frustrates, or "tilts" a player. Put terms of SDT, "tilt" occurs when a player's competence need satisfaction is directly (and repeatedly) threatened, resulting in frustration and increased aggression. While in this frustrated state, desperation to satisfy competence needs is heightened, encouraging players to pursue more high-risk-high -reward strategies, many of which inevitably fail. These failures further represent threats to competence, which further frustrates players, and so on. In our study, it may be that toxic behavior from confederates extrinsically "tilted" teammates, and therefore worsened performance. Whereas in our study confederates were randomly assigned to a systematically toxic condition, it may be that much of the toxic behavior experienced naturally in online gaming environments is, in fact, provoked by frustration at poor performance. In this sense, our results suggest that players should actively resist the urge to express their frustration with poorly performing teammates, as doing so only worsen matters.

Limitations and future directions

A potential limitation in our study is the unmeasured effects of confederate performance on team performance. Although we purposefully omitted confederate performance from measures of team performance by averaging statistics for team performance excluding the statistics for confederate performance, the indirect effect of confederate performance on others' performance, and thus team performance, is unavoidable. In fact, confederate performance was found to be significantly influenced by experimental condition, with almost double the effect size relative to the average participant (Pillai's Trace = .060, $F(4,174) = 2.778$, $p = .029$, $\eta^2 = .060$.) We believe there may be two main factors that drove the strength of this difference. 1) The act of being toxic likely harmed confederate performance, as time spent flaming teammates was time not spent actively focusing on game objectives. However, this effect should not be unique to this experiment and represents a natural extension of the effects of toxic behavior. Regardless, future research should further investigate the impacts of toxic behavior on the performance of those directly engaging in toxic behavior. 2) In addition, we believe the strength of this relationship is mostly a product of, rather than a source of, the worsened performance of participants in general, especially as confederates exclusively played supports. Due to the relative lack of agency in the support role (specifically enchanter-style supports, such as Janna and Soraka), supports are the most reliant upon the performance of teammates to perform themselves. This suggests than an effect expected to hamper team and individual performance should be exaggerated for supports. While our confederates played supports out of familiarity of the role and a desire to minimize the effect of confederate performance on game outcome, a replication of this study, perhaps placing confederates in a more autonomous role, may strengthen findings.

Another potential limitation is that the toxic behavior of other participants was not controlled for or measured in our study. It may be that the toxic behavior of other participants, and not the confederate, reduced individual and overall team performance. Previous work on toxic contamination (Neto et al., 2017) suggests that toxic behavior often elicits toxic retaliation from others, and was expected (Felps et al., 2006). This spread of toxic behavior could certainly have exacerbated our effect of the toxic behavior of confederates, but it also would weaken our effect in cases of toxic contamination in neutral conditions. Toxic contamination is a natural element to toxic behavior and is not specific to this experiment. Therefore, the mechanisms of toxic contamination – although unmeasured in our study – are simply an extension of, rather than a confound of, our effect. Regardless, future research should investigate more specifically the spread of toxic behavior in these environments, and its resultant influence on performance.

Motivation data had a strong response bias, as players who responded to post-game questions outperformed participants who did not respond ($t(714) = -3.49$, $p = .001$). Better performance likely induced positive moods, and positive moods increase helpful behavior (Carlson, Charlin, & Miller, 1988). Therefore, participants who had performed well were more willing to assist research confederates in the post-game questionnaire, and poorly-performing participants are underrepresented in our motivation data. Likewise, only a small number of participants reported the achievement motivation (N = 39), which was the most theoretically interesting category of motivation. These limitations made finding a statistically significant interaction unlikely. While we avoided playing games in ranked environments to protect the interests of participants (ranked environments involve participants gaining and losing ranking points within the game, which *LoL* players highly value), we believe our sample lacked achievement-motivated players as a result. Future research within the *LoL* environment, but nested in ranked rather than unranked environments, may hold a higher percentage of players who self-report achievement motivations, and be better equipped to draw inferences about a potential moderating effect of motivation (and the psychological need for competence) on toxic behavior and performance.

We believe that this study is an important contribution to the broader conversation on toxic behavior in online environments. To further explore the nature of toxic behavior, and potentially combat its prevalence in these environments, future research should investigate the process by which individuals may justify engaging in toxic behavior in online environments. It may be that individuals morally disengage themselves from their toxic behavior online (Bandura, 1999; Hartmann & Vorderer, 2010). If this is true, several different psychological processes could empower toxic justification, and therefore toxic behavior in individuals, including: perceptual biases (Lin & Sun, 2005; Watson, 2015); instantaneous negative character attribution (Haslam, 2006; Tetlock, 1985), perhaps influenced by in-group-out-group biases (Arsonson, 2012; Brewer, 1979); limited perspective-taking (Ku, Wang, & Galinsky, 2015; Yip & Schweitzer, 2019); dehumanization (Bastian & Haslam, 2011; Grietemyer & McLatchie, 2011; Haslam, 2006); and cognitive dissonance (Festinger, 1962). Understanding the potential relevance of these different cognitive processes could vastly inform new approaches to explaining and discouraging toxic behavior in online environments. In addition, conceptual replications of this study that explore toxicity in other online environments or the effects of positive, rather than toxic, players could significantly improve our understanding of how to develop healthier online environments.

Conclusion

Online gaming environments are becoming increasingly relevant to the general population, as multiplayer gaming environments such as *Overwatch, PUBG, Fortnite, Apex Legends, LoL, DOTA2, World of Warcraft*, and countless others, are continuing to grow in popularity. Considering how notorious these environments are for their toxic behaviors

(Holz Ivory et al., 2017), we must begin to understand the effects of these behaviors on those who experience them. Our study immediately builds upon previous research in this area by demonstrating that toxic behavior is causally detrimental to performance in addition to exploring the role of motivation on performance and toxic behavior. These results not only contribute to our understanding of the effects of toxic behavior on general performance, but also support the broader investigation of how to improve the social health of online environments.

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Data availability statement

The data that support the findings of this study as well as descriptive and correlational tables are available on Open Science Framework at https://osf.io/582vs/?view_only=82ac7607782e4df69098efaedadff263.

References

Aronson, E. (2012). *The social animal*. Worth Publishers. New York, NY.

Bandura, A. (1999). Moral disengagement in the perpetration of inhumanities. *Personality and Social Psychology Review*, *3*(3), 193–209. doi:10.1207/s15327957pspr0303_3

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, *44*(1), 1–26. doi:10.1111/j.1744-6570.1991.tb00688.x

Bastian, B., & Haslam, N. (2011). Experiencing dehumanization: Cognitive and emotional effects of everyday dehumanization. *Basic and Applied Social Psychology*, *33*(4), 295–303. doi:10.1080/01973533.2011.614132

Berkowitz, L. (1989). Frustration-aggression hypothesis: Examination and reformulation. *Psychological Bulletin*, *106*(1), 59. doi:10.1037/0033-2909.106.1.59

Blackburn, J., & Kwak, H. (2014). STFU-NOOB! Predicting crowdsourced decisions on toxic behavior in online games. *Proceedings of the 23rd international conference on world wide web*, Seoul, Republic of Korea, 877–888. https://doi.org/10.1145/2566486.2567987

Breuer, J., Scharkow, M., & Quandt, T. (2015). Sore losers? A reexamination of the frustration–aggression hypothesis for colocated video game play. *Psychology of Popular Media Culture*, *4*(2), 126–137. doi:10.1037/ppm0000020

Brewer, M. B. (1979). In-group bias in the minimal intergroup situation: A cognitive-motivational analysis. *Psychological Bulletin*, *86*(2), 307. doi:10.1037/0033-2909.86.2.307

Carlson, M., Charlin, V., & Miller, N. (1988). Positive mood and helping behavior: A test of six hypotheses. *Journal of Personality and Social Psychology*, *55*(2), 211–229. doi:10.1037/0022-3514.55.2.211

Carlson, P. (2013, September 12). *New League of Legends video uses stats to show how "rage doesn't win games"*. PC Gamer. Retrieved from http://www.pcgamer.com/new-league-of-legends-video-uses-stats-to-show-how-rage-doesnt-win-games/

Carron, A. V., Colman, M. M., Wheeler, J., & Stevens, D. (2002). Cohesion and performance in sport: A meta-analysis. *Journal of Sport and Exercise Psychology*, *24*(2), 168–188. doi:10.1123/jsep.24.2.168

Carver, C. S., & Harmon-Jones, E. (2009). Anger is an approach-related affect: Evidence and implications. *Psychological Bulletin*, *135*(2), 183. doi:10.1037/a0013965

Christopherson, K. M. (2007). The positive and negative implications of anonymity in Internet social interactions: "On the internet, nobody knows you're a dog". *Computers in Human Behavior*, *23*(6), 3038–3056. doi:10.1016/j.chb.2006.09.001

Cole, H., & Griffiths, M. D. (2007). Social interactions in massively multiplayer online role-playing gamers. *Cyberpsychology and Behavior*, *10*(4), 575–583. doi:10.1089/cpb.2007.9988

Comer, D., Baker, R., & Wang, Y. (2015). Negativity in massive online open courses: Impacts on learning and teaching and how instructional teams may be able to address it. *InSight: A Journal of Scholarly Teaching*, *10*, 92–113. doi:10.46504/10201508co

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1*(1), 16. doi:10.1037/1082-989X.1.1.16

De Grove, F., Cauberghe, V., & Van Looy, J. (2016). Development and validation of an instrument for measuring individual motives for playing digital games. *Media Psychology*, *19*(1), 101–125. doi:10.1080/15213269.2014.902318

Demircioglu, M. A. (2018). Examining the effects of social media use on job satisfaction in the Australian public service: Testing self-determination theory. *Public Performance & Management Review*, *41*(2), 300–327. doi:10.1080/15309576.2017.1400991

Dodge, K. A., & Coie, J. D. (1987). Social-information-processing factors in reactive and proactive aggression in children's peer groups. *Journal of Personality and Social Psychology*, *53*(6), 1146. doi:10.1037/0022-3514.53.6.1146

Donaldson, S. (2017), I predict a riot: Making and breaking rules and norms in League of Legends. *Proceedings of digital games research association (DiGRA)*. http://www.digra.org/wp-content/uploads/digitallibrary/103_DIGRA2017_FP_Donaldson_Rules_Norms_LoL.pdf

Duggan, M. (2014, October 22). *Online harassment*. Pew Research Center, Washington, DC. Retrieved from http://www.pewinternet.org/2014/10/22/online-harassment/

Duggan, M. (2018, July 11). *Online harassment 2017*, Pew Research Center, Washington, DC. Retrieved from https://www.pewinternet.org/2017/07/11/online-harassment-2017/.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. doi:10.3758/BF03193146

Felps, W., Mitchell, T. R., & Byington, E. (2006). How, when, and why bad apples spoil the barrel: Negative group members and dysfunctional groups. *Research in Organizational Behavior*, *27*, 175–222. doi:10.1016/S0191-3085(06)27005-9

Festinger, L. (1962). Cognitive dissonance. *Scientific American*, *207*(4), 93–106. doi:10.1038/scientificamerican1062-93

Foo, C. Y., & Koivisto, E. M. (2004). Defining grief play in MMORPGs: Player and developer perceptions. *Proceedings of the 2004 ACM SIGCHI international conference on advances in computer entertainment technology*, Singapore, 245–250. doi: 10.1145/1067343.1067375

Fox, J., Gilbert, M., & Tang, W. Y. (2018). Player experiences in a massively multiplayer online game: A diary study of performance, motivation, and social interaction. *New Media & Society*, *20*(11), 4056–4073. doi:10.1177/1461444818767102

Fragoso, S. (2015). "HUEHUEHUE I'm BR": Spam, trolling and griefing in online games, Revista FAMECOS - Mídia. *Cultura E Tecnologia*, *22*(3), 37–53.

Greitemeyer, T., & McLatchie, N. (2011). Denying humanness to others: A newly discovered mechanism by which violent video games increase aggressive behavior. *Psychological Science*, *22*(5), 659–665. doi:10.1177/0956797611403320

Hartmann, T., & Vorderer, P. (2010). It's okay to shoot a character: Moral disengagement in violent video games. *Journal of Communication*, *60*(1), 94–119. doi:10.1111/j.1460-2466.2009.01459.x

Haslam, N. (2006). Dehumanization: An integrative review. *Personality and Social Psychology Review*, *10*(3), 252–264. doi:10.1207/s15327957pspr1003_4

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, *6*(2), 65–70.

Holz Ivory, A., Ivory, J. D., Wu, W., Limperos, A. M., Andrew, N., & Sesler, B. S. (2017). Harsh words and deeds: Systematic content analyses of offensive* user behavior in the virtual environments of online first-person shooter games. *Journal for Virtual Worlds Research*, *10*(2), 2. doi:10.4101/jvwr.v10i2.7274

Huber, P. J. (1981). *Robust statistics*. John Wiley, New York, NY.

Human, L. J., & Biesanz, J. C. (2011). Through the looking glass clearly: Accuracy and assumed similarity in well-adjusted individuals' first impressions. *Journal of Personality and Social Psychology*, *100*(2), 349. doi:10.1037/a0021850

Jeng, S., & Teng, C. (2008). Personality and motivations for playing online games. *Social Behavior and Personality*, *36*(8), 1053–1060. doi:10.2224/sbp.2008.36.8.1053

Joinson, A. (1998). Causes and implications of disinhibited behavior on the Internet. In J. Gackenbach (Ed.), *Psychology and the Internet: Intrapersonal, interpersonal, and transpersonal implications* (pp. 43–60). Academic Press, Cambridge, MA.

Kasumovic, M. M., & Kuznekoff, J. H. (2015). Insights into sexism: Male status and performance moderates female-directed hostile and amicable behaviour. *Plos One*, *10*(7), e0131613. doi:10.1371/journal.pone.0131613

Kiesler, S., Siegel, J., & McGuire, T. W. (1984). Social psychological aspects of computer-mediated communication. *American Psychologist*, *39*(10), 1123. doi:10.1037/0003-066X.39.10.1123

Ku, G., Wang, C. S., & Galinsky, A. D. (2015). The promise and perversity of perspective-taking in organizations. *Research in Organizational Behavior*, *35*, 79–102. doi:10.1016/j.riob.2015.07.003

Kwak, H., Blackburn, J., & Han, S. (2015), Exploring cyberbullying and other toxic behavior in team competition online games. *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, Seoul, Republic of Korea, 3739–3748. https://doi.org/10.1145/2702123.2702529

Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence testing for psychological research: A tutorial. *Advances in Methods and Practices in Psychological Science*, *1*(2), 259–269. doi:10.1177/2515245918770963

Lapidot-Lefler, N., & Barak, A. (2012). Effects of anonymity, invisibility, and lack of eye-contact on toxic online disinhibition. *Computers in Human Behavior*, *28*(2), 434–443. doi:10.1016/j.chb.2011.10.014

Lee, C., & Chang, J. (2013). Does trust promote more teamwork? Modeling online game players' teamwork using team experience as a moderator. *Cyberpsychology, Behavior and Social Networking*, *16*(11), 813–819. doi:10.1089/cyber.2012.0461

LeJacq, Y. (2015, September 10). *A glimpse at League Of Legends' new system for reforming toxic players*. Kotaku. https://kotaku.com/a-glimpse-at-league-of-legends-new-system-for-reforming-1729847798.

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766. doi:10.1016/j.jesp.2013.03.013

Lin, H., & Sun, C. T. (2005), The "white-eyed" player culture: Grief play and construction of deviance in MMORPGs. *Proceedings of the 2005 digital games research conference, changing views: Worlds in play*.

March, E., & Marrington, J. (2019). A qualitative analysis of internet trolling. *Cyberpsychology, Behavior, and Social Networking*, *22*(3), 192–197. doi:10.1089/cyber.2018.0210

Muthén, B., & Satorra, A. (1995). Complex sample data in structural equation modeling. In P. V. Marsden (Ed.), *Sociological methodology* (pp. 267–316).

Neto, J. A., Yokoyama, K. M., & Becker, K. (2017). Studying toxic behavior influence and player chat in an online video game. *Proceedings of the International Conference on Web Intelligence*, Leipzig, Germany, 26-33. ACM. doi: 10.1145/3106426.3106452

Newton, R. R., & Rudestam, K. E. (1999). *Your statistical consultant: Answers to your data analysis questions*. SAGE Publishers, Newbury Park, CA.

Patchin, J. W., & Hinduja, S. (2010). Cyberbullying and self-esteem. *Journal of School Health*, *80*(12), 614–621. doi:10.1111/j.1746-1561.2010.00548.x

Perchied, P., Costigan, P., Lehman, M., & Moutinho, L. (2017, May 17). *Patch 7.10 notes*. Riot Games. Retrieved from https://na.leagueoflegends.com/en/news/game-updates/patch/patch-710-notes

Population Reference Bureau. (2013). *2013 world population data sheet*. Retrieved from http://www.prb.org/pdf13/2013-population-data-sheet_eng.pdf

Przybylski, A. K., Deci, E. L., Rigby, C. S., & Ryan, R. M. (2014). Competence-impeding electronic games and players' aggressive feelings, thoughts, and behaviors. *Journal of Personality and Social Psychology*, *106*(3), 441–457. doi:10.1037/a0034820

R Core Team. (2019). R: A Language and Environment for Statistical Computing. Vienna, Austria. Retrieved from https://www.R-project.org/

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. Sage Publications, Newbury Park, CA.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. doi:10.1037/0003-066X.55.1.68

Ryan, R. M., Rigby, C. S., & Przybylski, A. K. (2006). The motivational pull of video games: A self-determination theory approach. *Motivation and Emotion*, *30*(4), 344–360. doi:10.1007/s11031-006-9051-8

Scharkow, M., Festl, R., Vogelgesang, J., & Quandt, T. (2015). Beyond the "core-gamer": Genre preferences and gratifications in computer games. *Computers in Human Behavior*, *44*, 293–298. doi:10.1016/j.chb.2014.11.020

Shen, C., Sun, Q., Kim, T., Wolff, G., Ratan, R., & Williams, D. (2020). Viral vitriol: Predictors and contagion of online toxicity in world of tanks. *Computers in Human Behavior*, *108*, 106343. doi:10.1016/j.chb.2020.106343

Spil Games. (2013). *State of online gaming report*. Retrieved from http://www.spilgames.com/state_of_gaming_2013_uk_p1/

Suler, J. (2005). The online disinhibition effect. *Psychology of Cyberspace*, *7*(3), 321–326. doi:10.1089/1094931041291295

Tabachnick, B. G., Fidell, L. S., & Osterlind, S. J. (2001). *Using multivariate statistics*. Allyn and Bacon, Boston, MA.

Tang, W. Y., Reer, F., & Quandt, T. (2019). Investigating sexual harassment in online video games: How personality and context factors are related to toxic sexual behaviors against fellow players. *Aggressive Behavior*. doi:10.1002/ab.21873

Tassi, P. (2016, September 13), *Riot games reveals 'League of Legends' has 100 million monthly players*. Forbes. Retrieved from http://www.forbes.com/sites/insertcoin/2016/09/13/riot-games-reveals-league-of-legends-has-100-million-monthly-players/#7ed9746b10b1

Tetlock, P. E. (1985). Accountability: A social check on the fundamental attribution error. *Social Psychology Quarterly*, *48*(3), 227–236. doi:10.2307/3033683

Tseng, H., Ku, H., Wang, C., & Sun, L. (2009). Key factors in online collaboration and their relationship to teamwork satisfaction. *Quarterly Review of Distance Education*, *10*(2), 195–206.

Turnage, A. K. (2007). Email flaming behaviors and organizational conflict. *Journal of Computer-Mediated Communication*, *13*(1), 43–59. doi:10.1111/j.1083-6101.2007.00385.x

Warner, D. E., & Raiter, M. (2005). Social context in massively-multiplayer online games (MMOGs): Ethical questions in shared space. *International Review of Information Ethics*, *4*(7), 46–52.

Watson, M. (2015). A medley of meanings: Insights from an instance of gameplay in League of Legends. *Journal of Comparative Research in Anthropology and Sociology*, *6*(1), 225–243.

WePC. (2018). *2018 video game industry statistics, trends & data - the ultimate list*. Retrieved from https://www.wepc.com/news/video-game-statistics/#video-gaming-industry-overview.

World Bank Group. (2019). *Population, total*. Retrieved from https://data.worldbank.org/indicator/sp.pop.totl

Yee, N. (2006). Motivations for play in online games. *Cyberpsychology and Behavior*, *9*(6), 772–774. doi:10.1089/cpb.2006.9.772

Yip, J. A., & Schweitzer, M. E. (2019). Losing your temper and your perspective: Anger reduces perspective-taking. *Organizational Behavior and Human Decision Processes*, *150*, 28–45. doi:10.1016/j.obhdp.2018.07.003

Yip, J. A., Schweitzer, M. E., & Nurmohamed, S. (2017). Trash-talking: Competitive incivility motivates rivalry, performance, and unethical behavior. *Organizational Behavior and Human Decision Processes*, *144*, 125–144. doi:10.1016/j.obhdp.2017.06.002